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LYNN E. WOLAVER
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AFIT, Wright-Patterson AFB OH

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DISCRIMINATING BETWEEN GRADUATES AND FAILURES IN THE USAF MEDICAL LABORATORY SPECIALIST SCHOOL: AN EXPLORATIVE APPROACH

By

Mark D. Williams
Captain, USAF
1981

Pages in Thesis: 139.

Degree Awarded: Master of Science, Medical Technology

Institution: Mississippi State University

Approved
Capt K.S. Kurowski
AFIT 16 Dec 81

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ABSTRACT

MARK DAVID WILLIAMS, Master of Science, 1981.

Major: Medical Technology, Department of Biological Sciences

Title of Thesis: Discriminating Between Graduates and Failures in the USAF Medical Laboratory Specialist School: an Explorative Approach

Directed by: Barbara H. Turner, Ph.D.

Pages in Thesis: 139. Words in Abstract: 282.

ABSTRACT

The purpose of this study was to identify predictors of success in the USAF Medical Service Specialist school and to explore those characteristics that best differentiate Failures and Graduates. Composite scores from the Armed Services Vocational Aptitude Battery (ASVAB Form 6 and 7), a course-developed mathematics pretest score, a general intelligence score, and student demographics were used as predictors of the dicotomous criterion for 784 enlisted personnel entered into this occupational specialty. Group mean differences, correlation analysis, and the development of a linear discriminant function (LDF) were accomplished to determine those variables that best differentiated the two groups. Results of these analyses indicate that the most powerful predictor of graduation and discrimination between Graduates and Failures was the course-developed mathematics pretest. General intelligence, electrical aptitude, and age appear to offer additional predictive information. Distributions of the standardized discriminant scores in reduced-space appear to indicate a significant deviation from a normal distribution for the Failure population based on the variables studied. Recommendations are given that might help change the shape towards that of a normal distribution by the inclusion of noncognitive variables. Four separate classification schemes were utilized with cross-validation accomplished on a sample held out of the original computations of the LDF. Correct classification for Failures ranged between 31% to 67% and for Graduates between 89% to 94%. The two optimal classifications, under the criterion of a minimum of misclassification for the two groups, was accomplished via a graphic cutoff score procedure and when unequal a priori odds of group membership are taken into account in the classification functions. The use of a LDF is discussed in light of a proposed optimal aptitudes requirements system and for managerial control of a remedial program.

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A Thesis
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By

MARK D. WILLIAMS

APPROVED:

Barbara H. Turner

Barbara H. Turner, Ph.D.
Associate Professor of
Microbiology in Biological
Sciences (Major Professor)

James D. Yarbrough

James D. Yarbrough, Ph.D.
Professor and Head of Biological
Sciences (Graduate Coordinator)

Walter J. Drapala

Walter J. Drapala, Ph.D.
Professor of Statistics and
Head of the Department of
Agricultural and Experimental
Statistics (Minor Professor)

Edward L. McGlone, Ph.D.
Dean of the College of Arts
and Sciences

Walter B. Newsom

Walter B. Newsom, Ph.D.
Associate Professor of
Management (Committee Member)

Marion T. Loftin

Marion T. Loftin, Ph.D.
Vice President for Graduate Studies
and Research

Carol H. Williams

Carol H. Williams, M.S.
Assistant Professor of
Microbiology in Biological
Sciences (Committee Member)

December, 1981

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INTRODUCTION

Vocational counselors and organization selection and placement personnel have one desire that, in the majority of cases, would significantly improve their task. That is to identify a specific predictor of success for the respective position available. This is especially important for the young adult whose job experiences may be limited. In many cases, the career decisions made early in life are without much information about the tasks required on the job and researchers have found this to be the rule rather than the exception in the medical technology career field [Zufall, 1976; Youse and Clark, 1977; Gleich, 1978]. Unfulfilled expectations and inadequate abilities or aptitudes inevitably foster feelings of job dissatisfaction, lessened motivation, poor performance, or high attrition [Porter and Steers, 1973; Margolis *et al.*, 1974; Hoiberg and Pugh, 1978]. Any one of these conditions will exact a personal and organizational cost - a cost directly manifested in higher budgets and decreased organization effectiveness.

Concern with the prediction of training and job success in the military has increased during recent years. Selective budgetary constraints arising from Congressional action, the "all volunteer military", continued shortages of career oriented personnel, guaranteed job placement, and high attrition rates have necessitated valid and reliable placement procedures. The importance of the process can be appreciated by examining the possible costs of one training failure. Training facilities are located throughout the country. Retraining of the individual will convey costs across multiple budgets. Interservice support may be required to move the airman, his/her family and belongings to another area of the country. The strict bureaucratic nature of the organization requires lengthy administrative procedures, increased special instruction, and remedial interviews to assure the student fair treatment. Class slots are lost and the Air Force yield in productive employment is lowered. Also, the terminated student may suffer. Personal self esteem may be lowered, achievement motivation decreased, and the unmet expectations might arouse the desire to "get out" which can be a multiplicative function of cost for all concerned. These implications of poor placement mandate the need for a prediction of successful placement that not only addresses the knowledge of an individual's employment interests, but also an accurate estimate of the person's probability of successful training and job performance. It has been stated that the most objective may to assess probabilities of success are through the use of testing procedures. However, this . . .

> ". . . is not to say that tests have no faults, for they have many. Nevertheless, even though under some circumstances they favor certain classes of individuals rather than others, they are more impartial. Although the descriptions of the abilities and traits they give of one and the same individual do vary from one occasion to another, these descriptions are given with greater quantitative precision. And even though our knowledge about the usefulness of the various sorts of tests as aids in making occupational choices is woefully incomplete, it is vast compared with our knowledge about other procedures and devices"[Ghiselli, 1966].

A testing approach to placement has been the method of choice by the United States Air Force (USAF) since its inception in 1948. Guinn, *et al*. [1970b], in reviewing Air Force selection procedures, concluded that aptitude test scores were the best indicators that the USAF could use to predict success in technical training and Goslin [1964] judged it likely that tests play a much greater role in military personnel allocation than in any other occupational area. Thus, it would be appropriate that research be aimed at maximizing the efficiency and effectiveness of the aptitude measures used in USAF placement procedures. Methodological approaches for establishing an optimal aptitudes requirements system were offered by Maginnis et al. [1975]. Some specifics of such a system included:

> "Establish and maintain an optimal baseline set of valid aptitude requirements and quotas that meets personnel system needs. . .
>
> Be able to specify short-term aptitude requirements different from the optimal to allow total manpower quotas to be met . . .
>
> Be able to respond to long term personnel system changes with changes to the optimal baseline set of aptitude requirements. . .
>
> Meet needs of aptitude requirements system personnel for simplicity of administration, scoring, and interpreting aptitude measures while meeting rigorous standards of prediction. . .
>
> Encourage the utilization of lower aptitude personnel without compromising mission effectiveness. . .
>
> Deemphasize the role of purely secondary needs (e.g. academic proficiency) in setting selection and assignments criteria and emphasize the roles of those needs that contribute directly to mission success" [Maginnis et al., 1975].

In relation to training, they recommend that a survey be made of the characteristics of present training courses to determine the aptitude types and levels required to pass. As of this date, little research has been accomplished in this area.

This study is aimed at examining the "predictive characteristics" of courses J3ABR90430 and J5A2090450, Medical Laboratory Specialist at the USAF School of Health Care Sciences, Sheppard AFB, Texas. This occupational field can be chosen by a newly enlisted member (assuming available quotas) by meeting the following mandatory requirements:

1. Completion of high school subjects in chemistry and algebra.

2. Normal color vision as specified by Air Force Regulation 160-43.

3. A minimum aptitude level of 60 on the General Aptitude Index (GI) of the Armed Services Vocational Aptitude Battery (ASVAB) [AFR 39-1(C7), Attachment 50, 30 April 1980]

The course consists of two phases: Phase I ". . . is a 17-week course which trains students in the basic theory and skills, collection, preparation and analysis of biological fluids and other substances by standard procedures used in medical laboratories . . . Emphasis is placed on routine methodology employed in the fields of urinalysis, blood banking, serology, clinical chemistry, bacteriology, mycology, and parasitology" [Carroll, 1980]. Phase II is a 36-week course conducted at specific USAF hospitals primarily focused at instruction of clinical applications in the major fields of the laboratory.

Information available to course instructors include: ASVAB composite scores in Mechanical (MI), Administrative (AI), General (GI), and Electrical (EL) aptitudes; the Air Force Qualifying Test (AFQT); a general Mathematics Pretest; and student demographics. Based on this information, the purpose of this study is to:

1. perform an exploratory study of those variables presently available to course instructors in relation to a criterion of successful completion of Medical Laboratory Specialist (MLS) technical training,

2. examine the utility of a discriminant model for the prediction of graduation from MLS technical training,

3. conduct a classification and cross-validation procedure to estimate the stability of the model on an independent sample and to determine an estimate of the expected misclassification rate,

4. evaluate the appropriateness of the model in light of the optimal aptitude requirements system discussed by Maginnis _et al_. [1975].

REVIEW OF LITERATURE

History

Any effort designed to selectively place an individual in a specific catagory or treatment based on traits the person possesses requires some explicit assumptions about the nature of man. First, we must assume there are differences between human beings. Second, that these differences can be measured and evaluated. And third, that with some probability (at least better than chance) we can successfully predict a future outcome. In vocational prediction these differences were first classified as abilities. A review of the historical development of measuring human differences is given by Dunnette [1966] in Personnel Selection and Placement. His review is highlighted here.

Plato was probably the first person to write about differences in abilities and the need for an accurate system of assigning persons to particular occupations so that they could maximally contribute to society. However, adequate testing of human differences had to wait until appropriate mathematical models could be developed to objectively assess differences. In 1869, Sir Frances Galton in his book Hereditary Genius laid the foundation for these studies by developing a system for classifying individuals according to their abilities. He concluded that all human differences were distributed according to the known frequencies of the normal distribution by a standard score. With this theory, researchers began to measure human differences reflected in dimensions such as sensory and motor testing. However, Alfred Binet, in 1895, argued that more complex mental processes such as memory, imagery, imagination, attention, and comprehension should be studied. In 1905, he published the first Binet Test of Intelligence. Lewis Terman, at Stanford University, expanded on the Binet Test and published his Stanford-Binet in 1916. Scores on this test were expressed as an Intelligence Quotient (IQ). Utilizing more complex statistical models, Charles Spearman [1927] proposed that humans possessed not only a general intelligence factor but also a group of specific abilities. Factor analytic studies performed by L. L. Thurstone [1938] and G. P. Guilford [1956] extracted several factors that they felt accounted for the range of observable differences among individuals. Thurstone grouped the major cognitive abilities of man into seven catagories; verbal comprehension, word fluency, number aptitude, inductive reasoning, memory, spatial aptitude, and perceptual speed. Guilford saw mental organization lying along three dimensions; operations, contents, and products. Helmstadter [1964] summarized J. P. Guilford's conclusions as such: a person performing successfully all the operations containing semantic content would be said to have high verbal ability; a person performing all operations containing symbolic content would have high mathematics ability; one performing effectively operations with figural content would have high spatial or artistic ability; and a person who could recognize, remember, solve, and evaluate contents involving interpersonal behavior would be said to possess high social ability. Vernon [1960] pictured individual differences in cognitive abilities as resembling a branching tree of General Ability. The two main branches represented

Academic Ability and Practical Ability. The academic branch had smaller branches of Reasoning, Numerical, and Verbal Abilities. The practical branch had branches of Perceptual, Mechanical, and Spatial Abilities.

The development of present aptitude tests have been based on such conceptualizations. Thorndike and Hagen [1977] have noted that it was through the ". . . theoretical research on the nature of abilities on the one hand and applied research on the validity of specific tests for specific jobs on the other, psychologists have been guided in the design of aptitude test batteries for use in education and vocational guidance and in personnel selection and classification."

Validity of Occupational Aptitude Tests

In evaluating the usefulness of tests as aids in making occupational choices, the major concern is the extent to which they measure the abilities and traits important for success in the jobs under consideration.

Ghiselli [1966] sees face validity for occupational aptitude testing most likely originating with the Great War of 1914-1918. Standard tests were utilized to induct and assign thousands of soliders based on intelligence, aptitudes, and occupational skills. He sees the relative success of this program as moving testing to a high degree of sophistication, but also inferring a substantial over-rated accuracy to the layman. Objective validity measures have depended on the use of statistical correlation. As such, the occupational validity of a test is the accuracy with which the test scores predict the criterion. The higher the correlation, the higher the validity.

Research in the development and utilization of tests has been rather extensive. The technical considerations of psychometric theory are presented by various authors [Gulliksen, 1950; Lord, 1952; Guilford, 1954; Cronback *et al.*, 1972]. The most intensive integration of available information and data on the validity of occupational aptitude testing is given by Ghiselli [1966] in *The Validity of Occupational Aptitude Tests*. The validity correlations that he presents are based on the criterion of training success and level of job proficiency. His conclusions are presented here.

Ghiselli concludes that there exist three dimensions in terms of occupational validity; one of intellectual abilities and perceptual accuracy, one of motor abilities, and one of mechanical and spatial abilities. The first two are somewhat related but relatively independent of the third. He also addresses the predictive power of tests in relation to the criterion of training and that of job proficiency, with the following conclusions:

1. tests of perceptual accuracy and motor abilities are essentially the same for both criterion;

2. tests of intellectual abilities, i.e., intelligence, and in particular, arithmetic tests, are much more predictive of training than of proficiency criteria;

3. tests of spatial and mechanical abilities are more predictive of trainability;

4. general job success seems least well predicted by tests of motor abilities and best by tests of intellectual abilities.

Ghiselli did not offer any conclusions about personality or interest tests since the tests were of such a heterogenous group that his use of a mean validity coefficient would have been misleading. The relationship between mean validity coefficients for training and job proficiency, for all occupations taken together, was .14. Hence, he infers that a test may have relatively high validity for training on a given job and at the same time low validity for job proficiency [Ghiselli, 1966]. Studies presenting similar results on training versus job proficiency are given by Kapes [1971] and Herr _et al_. [1973].

The manual for the General Aptitude Test Battery (GATB) has reported various correlations of the GATB scores with success either in training or on-the-job. Correlations between the aptitude tests and their criterion were the basis for the establishment of qualifying scores that most effectively differentiated successful and unsuccessful workers. Comparing the correlations arrived at by Ghiselli with those of the GATB, it can be noted that Ghiselli's validity coefficients are, in general, less than that reported by the GATB. One possible explanation is given by Thorndike and Hagen [1977]. They felt that the pooled data used by Ghiselli may have diminished overall correlations by combining various jobs into fewer clusters than the GATB. However, it is also possible that such a large combination of jobs and coefficients provide a more stable picture of the true validity of occupational aptitude testing. They further note that the GATB data is less than ideal since it is concurrent (rather than predictive); the samples were small, the samples may have been from a single plant or company, and there was no independent cross-validation.

Ghiselli updated his 1966 summary of the occupational validity of tests in 1973. The range of validity coefficients for all jobs studied were: .28-.65 for training, and .24-.46 for job proficiency. These correlations are based on a single test with the criterion, combinations of particular tests may increase validity [Ghiselli, 1973].

An excellent review of technical and environmental considerations that may influence the overall validity of psychological tests in personnel selection and placement is given by French [1978]. He discusses the impact of criterion choice, test reliability, moral and legal issues, labor-management relations, technology, motivation and others, in test utilization. Thorndike [1949] has noted that there is no easy road to accurate placement decisions and that the ". . . worker in the field is continuously concerned with testing, verifying, and in improving the adequacy of his procedures."

Air Force Aptitude Tests Utilized in Selection and Placement

From 1959 to 1968, the Airman Qualifying Exam (AQE) was the aptitude battery used by the USAF. Tupes _et al_. [1967] in analyzing certain methods to improve the AQE have summarized the battery. The AQE became operational for testing of primary aptitudes used for screening, selective enlistment and classification of basic trainees in 1959. It consisted of 200 aptitude items which were summed to yield four aptitude composites; General (GI), Administrative (AI), Mechanical (MI), and Electronics (EL). Qualifying scores for each composite were: 40 on the GI, AI, and MI; and 60 on the EL. An acceptable score on any one or more composites (above cutoff) allows the applicant to enlist. The person is then assigned an area for which the person is qualified, has an interest, and for which a quota exists.

A number of follow-up studies were accomplished for predicting performance in technical training with correlation to final grades ranging between .6 to .7 [Lecznar, 1963; McReynolds, 1963; Lacznar, 1964; Madden and Lecznar, 1965]. Test bias was also evaluated. Tupes et al. [1967] in analyzing approximately 73,000 enlistees during 1961 found that somewhat different patterns of aptitudes and individual background were apparent within the broad career groups established. They concluded that separate aptitude composites for each course would increase validity. Lecznar [1962], Lecznar [1965] and Tupes [1965] found that individuals from different geographical areas differed considerably on aptitudes and other characteristics such as education and motivation to enlist. Gordon [1953] concluded that prediction of technical school grades were essentially the same for black and white students. However, Guinn et al. [1970a] in a study using 1,900 airmen found significant interaction between test scores and race. They found educational differences to be most highly related to performance on tests comprising general intelligence, with race differences having highest relationships with the mechanical composite scores. Differences in geographical areawere found to interact with a variety of the subtests. Guinn et al. [1970b] followed their initial study by examining 19,734 technical graduates in 30 different training courses to assess cultural subgroup differences. They found that the performance of blacks and high school non-graduates tended to be overestimated in prediction models as were individuals from the North-Northeast area. Persons from the Far West-Pacific Coast area tended to be underpredicted.

In 1968, the AQE was replaced by the Armed Services Vocational Aptitude Battery (ASVAB) in the military high school testing program [Vitola and Alley, 1968]. The ASVAB became the instrument for aptitude testing of all Air Force enlistees in 1973 and consisted of four aptitude composites and a general intelligence composite. Development of ASVAB Forms 1 through 4 is discussed by Jensen and Valentine [1976] and Bayroff and Fuchs [1970]. Vitola and Wilborn [1971], in analyzing bias in the earlier forms, found females scored slightly higher than males on the general intelligence composite (AFQT). Valentine and Massey [1976] found that females scored higher on the General and Administrative composites, while males scored higher on the Mechanical and Electrical composites. The early studies by Guinn were substantiated by Valentine [1977] in relation to demographic influence. However, in relation to minority overprediction, he noted that adjustments to prediction equations would essentially reduce the qualification rates for these individuals. Furthermore, he found the use of education background did contribute to prediction accuracy in some cases, but was subject to such bias in reporting that utilization in general prediction models did not seem appropriate.

ASVAB Forms 5, 6, and 7 were developed in 1976 [Jensen _et al_., 1976]. Kettner [1976] compared the ASVAB Form 5 with the GATB and the Differential Aptitude Tests (DAT). Criticism of the ASVAB test-retest reliabilities was given by Valentine and Massey [1976]. They concluded that the data strongly suggested non-standard operational testing during that time frame. The greatest amount of criticism has come from researchers on the use of ASVAB Form 5 for high school vocational counseling. Vanderploeg and Mueller [1978] felt the studies cited to support the use of ASVAB Form 5 were poorly executed and utilized sample sizes that were too small. On factor analysis of the subtests, they could only extract two factors. Factor 1 accounted for 51% of the total variance and Factor 2 less than 9%. Factor 1 had high loadings on 2/3 of all subscales and included all the vocational subscales. Factor 2 was associated with mathematics ability. Cronbach [1978] argued that some subtests were measures of experience and that the prediction of occupational aptitude based on information tests were inappropriate. He referenced Fletcher and Ree [1976] and noted that two major factors appear to emerge and that the Mechanical composite appeared to be a spatial plus general composite rather than mechanical. Valentine and Mathews, in response to this, offered evidence from their study in 1977 to support the job specific validity of the mechanical composite. They noted validity correlations of .29, .34, and .52 for three mechanical training programs with the mechanical composite. Validity correlations for the mechanical composite with training success in some administrative specialties did less well. Simm and Truss [1979] in examining the normalization procedure used for ASVAB Forms 6, 7 noted errors in the normalized scores. The percentile scores were found to be higher than actuality; however, the ranking of individuals remained the same. Correction of the reported normalized scores has been difficult due to a nonlinear relationship between actual and reported scores.

ASVAB Forms 8, 9, and 10 were developed and standardized by Fruchter [1977]. They became operational in October, 1980, and are presently in use. They are not affected by the normalization error noted in Forms 5, 6, and 7. A listing of the subtests and composites for the most recent ASVAB Forms (5,6,7,8,9,10) can be found in Appendix A.

Military Prediction Studies

Air Force studies in predicting success have almost exclusively relied on the criterion of technical course grades. Leisey and Guinn [1977] developed a model to help identify potential student failures in three medical specialties. Criterion data included type of eliminee (i.e., academic, medical, other), phase test scores, and final grade. Independent variables included; ASVAB composites, Otis-Lennon Mental Ability Test, Vocabulary score from the Word Clue Test, two reading ability scores, years of education, specialty preferred, whether guaranteed job placement, high school courses completed, age, and years of active service. Percentages of eliminees correctly predicted ranged from 8% to 34%. Linear multiple regression models were developed for full and restricted variable usage. It was noted that statistically significant increases in the multiple correlation were found by utilizing the full model and warranted the use of the commercial tests in prediction.

Hoiberg and Pugh [1978] utilized 39 variables comprised of life history items, motivation items, expectations, personality, and aptitudes to predict attrition for 7,923 enlisted Navy personnel within seven occupational specialties. The most powerful predictors included: education level, number of school expulsions and suspensions, two subscales of the Comrey Personality Test, arrests, age, aptitudes, and expectations.

Frederico and Landis [1979a] proposed the use of a discriminant model to predict the dicotomous criterion of Graduates and Failures in the Navy's Basic Electricity and Electronics school. Their sample consisted of 207 students, with independent variables consisting of measures of cognitive styles, abilities, and aptitudes. The data demonstrated that aptitudes alone predicted better than abilities or styles alone or in combination. Optimum classification was obtained utilizing aptitudes plus abilities or aptitudes plus abilities plus styles. As noted by the authors, cross-validation was needed. In further studies, Frederico and Landis [1979b] found successful completion of the course to be dependent upon space perception, general reasoning ability, and scores in mathematics, general science and automobile information.

A screening methodology for entry into the Security Police field was presented by Guinn _et al_. [1977]. They concluded that aptitudes, interests, and personal history data demonstrated predictive value in selection. Mathews and Jensen [1977] found the General composite of the ASVAB to correlate significantly with final grades in a Dental Laboratory Specialist course. A perceptual test composite was found to correlate with laboratory success. Other studies that have utilized the ASVAB include; Nuanez [1977], in which the General composite was a fairly good predictor of grade point average (GPA) in a high school, and

Henegar [1975], where the General and Electrical aptitude composites had the greatest degree of association with final grades in an Electronics Principles course.

Roark [1981b] developed a model from 113 student test scores in the USAF Medical Laboratory Specialist course utilizing a precourse math test and three arithmetic composites from the Tests of Basic Education (TABE). The criterion under study was the first chemistry exam (Block I-1). Cross-validation on an independent sample of 52 students was accomplished with an 88% predictive accuracy noted.

Prediction In the Clinical Laboratory

A review of early studies in aptitude and ability testing in the clinical laboratory has been accomplished by Zufall [1974]. Her review is presented here.

Zufall notes that the first published work in aptitude testing was accomplished by Strassel, in 1956. She utilized the Guilford-Zimmerman Temperament Survey, the Judgment and Comprehension Test from the Flanagan Aptitude Classification Battery for Biological Sciences and the ACE for guidance counseling of students. In 1958, the Colorado Department of Employment developed a specific aptitude battery for Medical Technologists to be used in the GATB. The aptitudes chosen, based on mean scores of participants and lowest standard deviations and correlations were; G-intelligence, V-verbal aptitude, P-form perception, and C-clerical aptitude. Champion, et al., in 1967, correlated GATB scores and GPA with MT (ASCP) national registry exam results and found the best predictor of score to be GPA. The best combination consisted of GPA plus V-verbal aptitude. The Strong Vocational Interest Blank (SVIB) was utilized by Rausch and McClune, in 1969, to test college freshman. They found that students who eventually completed the program demonstrated numerical and mechanical interests as well as a preference for the biological sciences. Furthermore, those freshman who eventually left the laboratory program showed a greater interest in social service than the medical technology graduates. In 1970, Eberfield and Love attempted to describe the basic characteristics related to success in medical technology. Utilizing a battery of psychological tests which included the Bell Adjustment Inventory, Kuder Perference Record, and the Selective College Ability Test (SCAT), they found successful students indicated a strong interest in science activities, dislike of persuasive activities, and had a slightly higher mean value on the aggressive scale of the Bell Adjustment Inventory than the normal population. The best single predictor of performance in their clinical year was past performance [Zufall, 1974].

Two studies not addressed by Zufall were accomplished by Duteman et al. [1966] at the University of Florida. They utilized the Florida Placement Exam (FPE), Strong Vocational Interest Blank (SVIB), Minnesota Multiphasic Personality Inventory (MMPI), Attitudes Towards Disabled Persons Test, and the verbal and quantitative portions of the SCAT to distinquish differences between Medical Technologists (MT), Occupational Therapists (OT), Physical Therapists (PT), Nurses (N), and other allied health workers (O), at their College of Health Related Professions. The subjects consisted of 206 students entering the Introduction to the Health Professions course during 1961, 1962, and 1963. The scores of eventual graduates from each field were used in a discriminant analysis procedure. They found that MT graduates as freshman scored higher on the mathematics subtest of the FPE and SCAT than PT, OT, and O. Factor analysis of the SVIB found laboratory technology loaded heavily on a separate factor than all other health related fields suggesting statistical independence from the other groups. Other professions that loaded high on this factor included; physicians, dentists, and mathmetics and science teachers. MT's also scored highest on the factor of decreased personal interaction and low on the personal interaction factors (opposite of the other health fields tested). Mahalanobis distances for MT-N, MT-O, MT-OT were substantially greater than any other comparison distances. Their MT subjects also scored higher on a masculine dimension (related to interest patterns). A career choice questionnaire, completed by all students as freshman, also noted a general lack of knowledge of the task requirements in the different health fields. They concluded that the FPE and achievement tests and SVIB discriminated among the groups, whereas the MMPI, SCAT, and Attitudes Towards Disabled Persons Test did not. The MT group was found to have the most accurate classification since they were farthest apart from all other groups in the discriminant analysis.

Duteman [1967] in another experiment, analyzed differences between the groups based exclusively on the MMPI. Utilizing discriminant analysis he was able to discriminate only MT's from the other health related professions (OT, PT, N, O). Best discrimination occurred on the Introversion Scale of the MMPI.

A review of the use of psychological tests on MT's was accomplished by Driver and Feeley [1974]. They concluded that MT's (overall) are inner directed, task oriented, associate with masculine interests, and have tradition-oriented values. They also discussed the results of a study at the University of Indiana that presented a model for predicting success in the clinical year of their medical technology program. Variables found to significantly correlate with success include GPA, age, quantitative chemistry course grade, organic chemistry course grade, introductory microbiology, and the medical microbiology lecture and laboratory course. Other variables that were originally utilized, but found not be significant in the model, were three other chemistry courses and six other biological science courses.

Personality characteristics associated with job satisfaction were investigated by French and Rezler [1976]. They used the Myers-Briggs Type Indicator (MBTI) to identify personality characteristics and the Job Description Index (JDI) to measure job satisfaction. The 154 subjects studied were all female and were separated into functional groups for comparisons (educators, clinical practice, and administrative). With the MBTI they found 20% of the respondents of the Introvert-Sensing-Thinking-Judging type (I-S-T-J). Their composite description of the I-S-T-J person is one who prefers attention to detail, careful exactness, system, order, concrete tasks, and they make decisions based on logic rather than emotions. Approximately 74% of the clinical practitioners are of the S-J type. They note that McCalley found the majority of dentists, physician assistants, and pharmacists in this category. A slight majority of all groups fall along the Introvert scale with administrators and educators differing significantly only on the Judging-Perceiving scale. They could make no definite conclusions about personality interactions with job satisfaction due to the small sample sizes within groups. However, they felt their data suggested no interaction.

Interpersonal values and job satisfaction was studied by Oliver [1978] using Gordon's Survey of Interpersonal Values (SIV). He concluded that:

1. MT's who value independence and recognition tend to be less satisfied with their job,
2. MT's who value benevolence and conformity tend to be more satisfied,
3. support and benevolence values are more likely bench level values,
4. MT's who value leadership are more likely to be in supervisory positions.

Leiken and Cunningham [1980] examined the predictive ability of the Allied Health Professions Admissions Test (AHPAT) for graduation from a School of Allied Health Professions and reviewed two previous studies reporting conflicting results on the utility of the AHPAT. Variables that were used other than the AHPAT composites were GPA and education level. The AHPAT composites of reading comprehension and chemistry appear to offer increases in predictability after inclusion of GPA and education level for MTs. Of all programs studied (cardiorespiratory science, medical technology, physician's assistants, and physical therapy), the AHPAT performed the poorest for the MT subjects. The highest R^2 was .22 for MTs, as opposed to values of .59 (PA), .48 (PT), and .47 (CRS) for the others.

Recently, Rifkin et al. [1981], at the University of Illinois, analyzed the factors presently utilized in their medical technology selection procedures. Academic factors consisted of sciences GPA, non-science GPA, a manual dexterity test, and a weighted sum of the science and non-science GPA. Non-academic factors included knowledge of occupation, career goals, interview, written ability, relationships with others, and problem solving skills. Their results, based on 52 graduates, were that the academic factors predicted the academic success criterion with validity coefficients of .61 with program GPA, .38 with their comprehensive exam, and .38 with the MT (ASCP) national registry exam. The non-academic factors correlated the highest witdh the criterion of hematology clinical success (.47), general clinical experience (.37), and microbiology clinical success (.30).

Two major limitations noted in almost all the studies presented are small sample sizes and the lack of cross-validation. The latter problem most likely a function of the first. This problem will most likely continue in light of the limited class sizes in the medical laboratory programs. However, this fact may not be so damaging, due to the consistent patterns that appear to emerge from the studies. General findings that appear to correlate highly with academic success are intelligence, numerical and verbal aptitudes, and high school grade point averages. Clinical success in the laboratory appears to be related to non-academic factors such as mechanical, perceptual, or spatial aptitudes. Job satisfaction and attrition (independently or interrelated) appear to be related to interpersonal values, interests, and/or personality. Also, evidence was presented that suggests that medical laboratory workers may require different aptitude levels, interpersonal styles, and interests than other allied health workers to be successful.

METHOD

Subjects

Data were available on essentially all enlisted personnel entering and completing courses J3ABR90430 and J5A2090450, Medical Laboratory Specialist (MLS) for two years prior to the 1981 fiscal year (FY). Although class rosters were available containing data prior to this date, substantiating records (ATC Form 156, Student Record of Training) for each student were maintained by administrative personnel for only the preceding two years. The original sample consisted of the 828 military personnel who entered course J3ABR90430 between 10 August 1978 to 15 December 1980. Students eliminated from the program for non-academic reasons (i.e., medical, administrative, predjudicial conduct, nonadaptability to military life, etc.) were not used in the data analysis which brough the final sample to 784 individuals.

Measures

Cognitive aptitude measures were obtained from the Armed Services Vocational Aptitude Battery (ASVAB) Form 6/7 which produce scores for cognitive aptitudes based on composites obtained from nine subtests, and a general intelligence score based on a composite of three subtests known as the Air Force Qualifying Test (AFQT) [Jensen _et al_., 1976]. Appendix A contains a listing and explanation of the subtests making up each composite. A general mathematics ability test (MPT) is administered to students after assignment to MLS technical training, but before the start of classes to help identify students possibly requiring increased special assistance.

The predictor variables utilized in this study were:

1. age at enlistment date (AGE)
2. years of education completed (YED), where 12 signifies high school completion, 13, one year of college, 14, two years of college, etc.
3. general intelligence, as measured by the AFQT
4. mechanical aptitude (MI)
5. administrative aptitude (AI)
6. general aptitude (GI)
7. electrical aptitude (EL), as measured by the ASVAB
8. general mathematics ability, as measured by the MPT
9. class shift (Class A, B, C).

The first three variables, education, intelligence, and age, have shown predictive value consistently in military studies [Klieger et al., 1961; Plag, 1962; Lecznar, 1964; Goodstadt and Glickman, 1975; Hoiberg and Pugh, 1978; Sands, 1978]. Cognitive aptitudes are presently used as placement tools in the USAF and have been found to be related to attrition in technical training [McReynolds, 1963; Leisey and Guinn, 1977; Mathews and Jensen, 1977; Frederico, and Landis, 1979]. Roark [1981] found mathematics ability, as measured by the MPT and Tests of Basic Education (TABE), to be related to failure in the MLS technical training chemistry block. In addition, class shift was included due to an impression by a school administrator that the evening shift had a failure rate noticeably less than the other two daytime shifts. Variable descriptions are given in Table 1.

Criterion

A dicotomous criterion of Graduates/Failures was used in the study. Graduates were considered to be those students who completed both Phase I and Phase II training successfully. Failues were those students who were eliminated from either Phase I or Phase II training due to academic deficiency. Based on these definitions, 666 students were catagorized into Group 1 (Graduates) and 118 into Group 2 (Failures).

Analyses

The analyses were carried out in three parts. In the first part, significance tests for the differences between the means of all variables were computed for Graduates, Phase I failures, and Phase II failures, to determine if Graduates differed from Failues and to determine whether Phase I Failures differed from Phase II Failures. This was accomplished by performing a one-way analysis of variance for each variable. If the multisample hypothesis of equal group means was rejected, then a multiple comparison test of group means was used to assess specific group mean differences. Probability of Type I error was held at the .05 level for group mean differences and for individual pairs of means in multiple comparisons. Also, point biserial product moment correlations were obtained for all continuous variables with the dicotomous Graduate/Failure criterion to evaluate variable validity to graduation. Pearson product moment correlations were computed between variables to determine the degree of collinearity between them, and first-order partial correlations were computed due to the reported high correlations between the

TABLE 1. LIST OF VARIABLES

Variable Number	Variable Name	Type Variable	Description
Predictors			
1	Class shift A	Categorical	Indicates first dayshift class
2	Class shift B	Categorical	Indicates second day-shift class
3	Class shift C	Categorical	Indicates night class
4	Age at enlistment	Continuous	Age of student trainee at time of enlistment
5	Years of education	Continuous	Number of years of education completed
6	AFQT score	Continuous	Percentile score derived from the AFQT/ASVAB; a measure of general mental ability
7	Mathematics Pretest score	Continuous	Course-developed general mathematics test
8	Mechanical Aptitude score	Continuous	Percentile score derived from ASVAB subtests
9	Administrative Aptitude score	Continuous	Percentile score derived from ASVAB subtests
10	General Aptitude score	Continuous	Percentile score derived from ASVAB subtests
11	Electrical Aptitude score	Continuous	Percentile score derived for ASVAB subtests
Criterion			
1	Graduate	Discrete	Student who successfully completed course J3ABR90430 and J5A2090450
2	Failure	Discrete	Student who was academically dismissed from either course J3ABR90430 or J5A2090450

aptitude composites [Vanderploeg and Mueller, 1978; Cronbach, 1978]. The amount of reduction in the validity correlations, when the influence of another highly correlated variable is partialed out, allows one to evaluate the significance of information in the non-constant variables not associated with the partialed variable [Guilford and Fruchter, 1978]. In this way, an indirect approach is taken to evaluate specific subtest validity to the criterion.

In the second part, a discriminant analysis was performed on the two-group criterion. An explorative approach was taken in the development of the linear discriminant function. As such, all variables were included in the model. For classification purposes, two classification rules were initially proposed. In the first, it was assumed that students had an equal probability of graduation or failure. In the second, a Baysian adjustment of the probability was made to the *a priori* probabilities of group membership [Cooley and Lohnes, 1971; Overall and Klett, 1972; Lachenbruch, 1975; Hull and Nie, 1979]. Due to peculiarities in the data, two alternative classification rules, graphic and quadratic methods, are also presented. Furthermore, an examination of the standardized discriminant scores was accomplished to explore the group overlaps and distributions.

In the third part, the resulting classification rules were applied to an independent sample that was held out of the sample used to develop the linear discriminant function. In this way, an estimate of the expected misclassification rate can be determined [Eisenbeis and Avery, 1972; Lachenbruch, 1975].

RESULTS

Evaluation of Means

The first objective of this study was to explore the significance of the variables selected in predicting graduation or failure from the MLS course. The initial approach was to assess differences (Table 2) between graduates and failures based on results achieved on aptitude and ability tests, age, and education level. A pairwise deletion procedure was used to incorporate as much of the data as possible. Under pairwise deletion, a case is omitted from the computation only if the variable being considered is missing. A case will therefore be included in all computations for which it has complete data. Mean differences between Graduates, Phase I and Phase II Failures were tested by a one-way analysis of variance and, if significant at the .05 level, were compared for specific differences using the Least-Significant Difference (LSD) procedure (Steel and Torrie, 1960). By this method, significant differences between Graduates and Phase I Failures were found on seven of the eight variables compared (Table 3). Phase I and Phase II Failures differed significantly only in mechanical aptitude (MI). When Phase I and Phase II Failures are combined (Table 4), significant differences, except for age at enlistment, remained between the two groups. The two group differences were tested for significance using Student's t statistic [Zar, 1974]. Class codes were subjected to a chi-square

TABLE 2. MEANS, STANDARD DEVIATIONS, AND SIGNIFICANCE TESTING FOR DIFFERENCES BETWEEN ALL GROUPS+

Variables	Graduates (n=)		Failures Phase I		Failures Phase II		F
	M	S.D.	M	S.D.	M	S.D.	
AGE	(654) 20.69	3.02	(105) 20.33	2.93	(12) 18.67	1.56	3.22*
YED	(654) 12.82	1.19	(99) 12.55	.92	(12) 12.33	.65	3.25*
MPT	(648) 85.78	12.52	(105) 65.64	18.04	(12) 70.83	22.47	103.9***
AFQT	(568) 70.23	14.95	(93) 58.45	10.48	(12) 58.83	10.62	29.6***
MI	(660) 54.08	25.26	(105) 38.33	18.39	(12) 54.58	19.12	18.9***
AI	(657) 75.08	16.46	(103) 67.96	18.86	(12) 62.92	16.85	10.6***
GI	(661) 80.62	11.45	(105) 71.95	10.08	(12) 77.5	9.17	27.1***
EL	(657) 70.91	18.34	(103) 53.54	17.62	(12) 56.25	22.88	42.7***

+one-way analysis of variance between Graduates, Phase I Failures, and Phase II Failures.

*p < .05

***p < .001

TABLE 3. DIFFERENCES BETWEEN ALL PAIRS OF MEANS

Variable	Means/Group		Differences*
AGE	18.67	Phase II Failures	a
	20.33	Phase I Failure	ab
	20.69	Graduates	b
YED	12.33	Phase II Failure	ab
	12.55	Phase I Failure	b
	12.82	Graduates	a
MPT	65.64	Phase I Failure	a
	70.83	Phase II Failures	a
	85.78	Graduates	b
AFQT	58.45	Phase I Failure	a
	58.83	Phase II Failure	a
	70.23	Graduates	b
MI	38.33	Phase I Failure	a
	54.08	Graduates	b
	54.58	Phase II Failure	b
AI	62.92	Phase II Failure	a
	67.96	Phase I Failure	a
	75.08	Graduates	b
GI	71.95	Phase I Failure	a
	77.50	Phase II Failure	ab
	80.62	Graduates	b
EL	53.54	Phase I Failure	a
	56.25	Phase II Failure	a
	70.91	Graduates	b

*Group means not having a letter in common differ significantly at P=.05 as judged by the Least Significant Difference Method.

TABLE 4. MEANS, STANDARD DEVIATIONS, AND SIGNIFICANCE TESTING FOR DIFFERENCES BETWEEN GRADUATES AND FAILURES (PHASE I AND PHASE II COMBINED)

Variables	Graduates		Failures		t
	M	S.D.	M	S.D.	
	(654)		(117)		
AGE	20.69	3.02	20.16	2.86	1.75
	(654)		(111)		
YED	12.82	1.19	12.52	.89	2.48*
	(648)		(117)		
MPT	85.78	12.52	66.17	18.50	14.36***
	(568)		(105)		
AFQT	70.23	14.95	58.5	10.44	7.7***
	(660)		(117)		
MI	54.08	25.26	40.0	19.04	5.75***
	(657)		(115)		
AI	75.08	16.46	67.43	18.65	4.5***
	(661)		(117)		
GI	80.62	11.45	72.52	10.1	7.17***
	(657)		(115)		
EL	70.91	18.34	53.83	18.14	9.23***

*$p < .01$

***$p < .001$

analysis and the hypothesis of independence was accepted at the .05 level (χ^2=.673 with 2 degrees of freedom (df)).

In general, Graduates have a slightly higher level of education, and score higher on tests of intelligence, numerical ability, and aptitudes than Failures. Failures in Phase II appear to be more like Failures in Phase I than they are to Graduates, but on the average are younger than both Graduates and Phase I Failures. The largest differences between the two groups was on the MPT, EL, and AFQT, with the Graduates scoring significantly higher than the Failures. Class shift is not found to be related to any group inparticular.

Validity Correlations

Pearson product moment correlations (pmc) were computed between all predictor variables to evaluate their degree of collinearity. A symmetric matrix of these correlations is shown in Table 5. It can be seen that all correlations between test scores are positive and range from .16 to .80, demonstrating moderate degrees of collinearity. Each correlation was tested for significance greater than zero by means of Fisher's t ratio [Guilford and Fruchter, 1978]. In all cases, the correlations between test scores were significant at the .001 level.

Point biserial pmc's were computed to assess the relationship of each variable to the criterion of graduation. The higher the correlation, the greater the linear relationship between the variable and the criterion. Thus, for high positive correlations, the higher the test score, the greater the probability of being a graduate and the greater

TABLE 5. CORRELATIONS BETWEEN PREDICTOR VARIABLES (n=641)

	CA	CB	AGE	YED	MPT	AFQT	MI	AI	GI	EL
CA	1.0									
CB	-.94*	1.0								
AGE	.01	.00	1.0							
YED	-.00	.00	.57*	1.0						
MPT	.08	-.07	-.05	.08	1.0					
AFQT	.06	-.05	.12	.11	.49*	1.0				
MI	.05	-.04	.05	.04	.36*	.58*	1.0			
AI	.08	-.06	.02	.15*	.36*	.32*	.16*	1.0		
GI	.06	-.05	.08	.05	.46*	.80*	.48*	.41*	1.0	
EL	.06	-.05	.01	.04	.51*	.77*	.69*	.18*	.58*	1.0

*p < .001, correlation not equal to zero.

that test's validity to the criterion. The aptitude test composites for ASVAB Form 6/7 are:

1. AFQT (WK + AR + SP)
   a. Word Knowledge (WK)
   b. Arithmetic Reasoning (AR)
   c. Spatial Perception (SP)

2. Mechanical (MI) (AI + MC + SI)
   a. Automotive Information (AI)
   b. Mechanical Comprehension (MC)
   c. Shop Information (SI)

3. Administrative (AI) (WK + AD + NO)
   a. Word Knowledge
   b. Attention to Detail (AD)
   c. Numerical Operations (NO)

4. General (GI) (WK + AR)
   a. Word Knowledge
   b. Arithmetic Reasoning

5. Electronics (EL) (AR + SP + EI)
   a. Arithmetic Reasoning
   b. Spatial Perception
   c. Electronics Information (EI) [DOD, 1976].

Because of the moderate overlap between subtests within the composites, a partial correlation procedure was accomplished to partial out the linear effects of a composite. Then the correlation to graduation of the remaining variables was recalculated by

$$r_{ij.k} = \frac{r_{ij} - (r_{ik})(r_{jk})}{\sqrt{1 - r_{ik}^2 \cdot 1 - r_{jk}^2}}$$

where k is the control variable, i and j are the independent and dependent variables, and r is the zero-order pmc [Guilford and Fruchter, 1978]. The results of the zero-order and first-order partial correlations are shown in Table 6. It can be seen (Table 6) that all variables have a positive correlation with graduation. The MPT, AFQT, EL, and GI appear to demonstrate the largest validity to graduation. Significant reductions in correlations occur when certain tests are held constant. When the information contained in the MPT is held constant, the aptitude composites AI, GI, and AFQT are reduced to less than .1. When EL is held constant, the AFQT, AI,and MI are reduced to less than .1. The partialing of AFQT reduces MI, AI, and GI, but is less effective than the MPT in reducing the EL. The GI reduces the AI significantly, but is less effective than the EL, AFQT, or MPT. The correlation of the GI reduces to .1 or less when the arithmetic reasoning subtest is partialed out by the AFQT or EL, indicating that the word knowledge subtest may be constant in the group. This would not be inconsistent with preselection based on the GI. Inferring from correlation reductions and variable

TABLE 6. POINT BISERIAL CORRELATIONS AND PARTIAL CORRELATIONS TO GRADUATION

Variables		Point Biserial (n=638)							
		AGE	YED	MPT	AFQT	MI	AI	GI	EL
		.04	.08	.45*	.28*	.25*	.15*	.27*	.33*
First-order Partials (n=641)	AGE	--	.06	.45*	.28*	.25*	.15*	.26*	.33*
	YED	-.00	--	.44*	.28*	.25*	.14*	.26*	.32*
	MPT	.07	.05	--	.08	.10	-.01	.08	.13*
	AFQT	.01	.05	.37*	—	.11	.07	.07	.17*
	MI	.03	.07	.39*	.18*	--	.12	.17*	.22*
	AI	.04	.05	.42*	.25*	.23*	—	.23*	.31*
	GI	.02	.06	.38*	.12*	.14*	.05	--	.22*
	EL	.04	.07	.34*	.05	.03	.10	.10	--

*p < .001, correlation greater than zero.

significance to graduation, it appears that the most powerful predictor is the MPT (lowest validity: .34). Also, the EL or AFQT are the only other variables to offer any appreciable validity. Since the AFQT is reduced more by the EL than vice versa, it appears that the EL may offer slightly more predictive power than the AFQT.

Discriminant Model Development

The second objective of this study was to examine the utility of a discriminant model for the prediction of MLS Graduates and Failures. The discriminant analysis procedure utilized for this study was computed using the Statistical Package for the Social Sciences, (SPSS Level 8) [Nie et al., 1975; Hull and Nie, 1979]. The purposes of a discriminant analysis are: (1) to test for mean group differences and to describe the overlaps between the groups, and (2) to develop classification schemes based on a set of p variables in order to assign previously unclassified observations into appropriate groups [Eisenbeis and Avery, 1972]. Thus, for exploratory purposes, it has both descriptive and predictive utility. In the two group case, the discriminant analysis attempts to form a linear combination of the p variables of the form

$$Y_i = a_1 z_{1i} + a_2 z_{2i} + \cdots\cdots\cdots + a_p z_{pi}$$

where $i = 1,2,\ldots,n.$, Y_i is the discriminant score, the a's are the weighting coefficients, and the z's are the standardized values of the p discriminating variables used in the analysis. The problem becomes the determination of optimal weighting coefficients such that the distance between the mean scores for the two groups is maximized relative to the variance within the groups. The underlying assumptions for this procedure are that the two groups being studied are; (1) discrete and identified, (2) each observation in each group can be described by a set of measurements on p variables, and (3) the variables have a multivariate normal distribution in each population [Eisenbeis and Avery, 1972]. A brief review of the computational steps required for deriving the linear discriminant function (LDF) for two groups is given in Appendix B. More complex mathematical treatments for the two group and the n group cases can be found in various texts [Tatsuoka, 1971; Cooley and Lohnes, 1971; Lachenbruch, 1975].

Subsample Selection

The total sample of 784 subjects was randomly split into two subsamples. This was accomplished by generating a random sample of uniformly distributed numbers from 0 to 1.66 and truncating the decimal portion. By this method, approximately 60% of the total sample would be coded zero and assigned to subsample 1 and the other 40% coded one and assigned to subsample 2 [Hull and Nie, 1979]. The first subsample was used to develop the discriminant function, while the second was used for cross-validation. Those subjects who had at least one missing discriminating variable were excluded from model development, but were used in classification. In case of missing values during classification, the group mean score for the respective group and variable was used to replace the missing variable value [Chan and Dunn, 1972]. The breakdown of the total sample is as follows:

784 cases used for the total analysis
474 cases selected for subsample 1 (SS1)
  88 cases were excluded from SS1 due to missing values
  386 were used for model development
310 cases were selected for subsample 2.

Procedure

A stepwise procedure for variable inclusion into the model was accomplished based on the criterion of reduction of Wilk's lambda. In general, SPSSWILK'S attempts to obtain a smaller overall Wilk's lambda than was obtained at an earlier step which used the same number of variables. Computational formulation and procedural steps as used in the SPSSWILK'S selection method is given by Gondek [1981]. A corresponding F statistic [Rao, 1965] is used to test the significance of the decrease in Wilk's lambda resulting from the addition of some new variable. For this study, the variable tolerance level was set at .001 (default), minimum F-to-enter 0.0, and F-to-remove 0.0. The null F values were used so that all variables would be entered into the analysis in a stepwise manner. Table 5 shows the general descriptive statistics for the subsample used in development of the LDF.

It can be seen that the means and standard deviations of the development subsample, shown in Table 7, compare favorably with those calculated from the total sample.

TABLE 7. GROUP MEANS AND STANDARD DEVIATIONS OF THE VARIABLES USED IN THE SUBSAMPLE FOR LDF DEVELOPMENT

Variables	Graduates		Failures	
	M	S.D.	M	S.D.
Class A	.52	.50	.47	.50
Class B	.44	.50	.52	.50
AGE	20.52	2.79	19.92	2.32
YED	12.80	1.19	12.48	.91
MPT	85.37	13.19	67.09	19.05
AFQT	70.79	14.93	57.94	9.10
MI	55.79	25.24	41.09	18.55
AI	75.14	16.92	65.0	18.49
GI	81.51	11.68	72.50	10.20
EL	71.58	18.74	54.06	18.49

Individual group covariance matrices were computed and tested for equality utilizing Box's M statistic and its associated approximate F test [Cooley and Lohnes, 1971]. The matrices were found to be significantly different at a confidence level less than .001 (Box's M = 136.65, F = 2.34, with 55 and 42033 df). Various researchers have noted that the quadratic rule is the appropriate one to use in cases of differing covariance matrices; however, the improvement in classification varies from case to case [Eisenbeis and Avery, 1972; Lachenbruch, 1975]. Thus, a quadratic discriminant function and classification rule was also developed. Computer output for this analysis can be found in Appendix F.

The following linear standardized discriminant function coefficients were developed:

Class shift A (V1)	-.36386
Class shift B (V2)	-.44812
Age at enlistment (V3)	.18136
Years of educatin (V4)	.08866
AFQT (V5)	.10871
MPT (V6)	.71745
MI (V7)	-.06417
AI (V8)	.09331
GI (V9)	.03553
EL (10)	.27587

Table 8 shows a comparison of three methods for determining the amount of contribution of each variable to discrimination between the two groups. The univariate F test approximates the relative discriminatory power of each variable by comparing the significance levels of the univariate analysis of variance F test for each variable to the criterion [Eisenbeis and Avery, 1972]. However, this procedure for choosing variables to be included in the model fails to consider the correlations between the variables [Cochran, 1964], which are moderate for this data. Using the standardized discriminant coefficients from a full variable model, the discriminatory power of individual variables can be evaluated in a manner similar to the method of beta weights in regression analysis [Goldberger, 1964]. However, for highly correlated variables the coefficients will be

TABLE 8. METHODS TO DETERMINE SIGNIFICANCE OF VARIABLES IN DISCRIMINATION

Order of Significance Highest to Lowest	Univariate F Test		Standardized Discriminant Coefficients		Wilk's Conditional Stepwise Entry		
	Variable	F	Variable	Std. Weights	Variable	Wilk's Lambda+	F to Enter
#1	MPT	86.97***	MPT	.71745	MPT	.815335	86.97
2	EL	46.87***	Class B	-.44812	AFQT	.80082	6.94
3	AFQT	44.10***	Class A	-.36386	AGE	.79406	3.2
4	GI	33.03***	EL	.27587	EL	.79091	1.5
5	MI	19.58***	AGE	.18136	Class A	.78876	1.0
6	AI	18.58***	AFQT	.10871	Class B	.78624	1.2
7	YED	4.07***	AI	.09331	AI	.78464	.77
8	AGE	2.6	YED	.08866	YED	.78383	.39
9	Class B	1.2	MI	-.06417	MI	.78346	.18
10	Class A	.60	GI	.33553	GI	.78338	.03

***$p < .001$

+all significant $p < .001$.

unstable and hard to interpret [Morrison, 1969]. The importance of class code in the standardized discriminant coefficients might then be suspect due to their high correlation and their lack of importance as predictors of graduation in earlier results. The stepwise procedure utilized for variable inclusion (SPSSWILK'S) is the Conditional Test that is based on variables already included in previous steps. Analysis of the reduction in Wilk's lambda, noted in Table 8, show that discrimination after the inclusion of MPT, AFQT, AGE, and EL is negligible. Also, the F-to-enter after the inclusion of EL is reduced to 1.0 which is the SPSS DISCRIMINANT default minimum F-to-enter. In referring to packaged discriminant programs, Gondek [1981] has recommended that the best procedure for variable inclusion when using a stepwise procedure is to use the threshold default values supplied by the package, since no simple rules exist for determining entry or removal thresholds for partial F's, tolerance statistics, or any of the other statistical criteria used in the stepping procedures. Thus, the only variables that would be entered into the model under default thresholds would be MPT, AFQT, AGE, and EL.

It is apparent that, by any method, discrimination is dominated by the MPT. Either AFQT or EL appear to offer the second best discriminatory power depending on which is entered into the equation first.

Distributions of the Discriminant Scores

Discriminant scores were derived using the standardized discriminant coefficients and the subject scores which have been converted to standard form (z-scores). As such, the discriminant scores produced are in standard form. So, over all cases in the analysis, the scores from the discriminant function will have a mean of zero and a standard deviation of one. Any single score then represents the number of standard deviations that the case is away from the mean for all cases. Group means can be found by averaging the scores for the cases within each group. The SPSS generated frequency histogram for Graduates (Group 1) and Failures (Group 2) is shown in Figure 1 and Figure 2, respectively. Under the assumption of multivariate normal distributions for the discriminating variables in the linear function, the reduced discriminant scores should also be normally distributed. An examination of the histogram for Graduates demonstrates a slight negative skew. The mean for this distribution then is pulled toward the skewed end [Guilford and Fruchter, 1978]. In the case of the Failures, shown in Figure 2, the distribution takes an apparent bimodal shape. A scaled drawing of the group dispersions and mean positions is shown in Figure 3. The plots show that the assumption of normality in the group populations does not hold and that a moderate degree of overlap exists. The negative implications of nonnormality would most likely be apparent in the classification results since the probabilities of group membership are based on the distribution of the normal density function.

FIGURE 1

WILLIAMS, 2-GROUP DISCRIM.
WILKS-ALL VARS IN-EQUAL

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

HISTOGRAM FOR GROUP 1

-- CANONICAL DISCRIMINANT FUNCTION 1 --

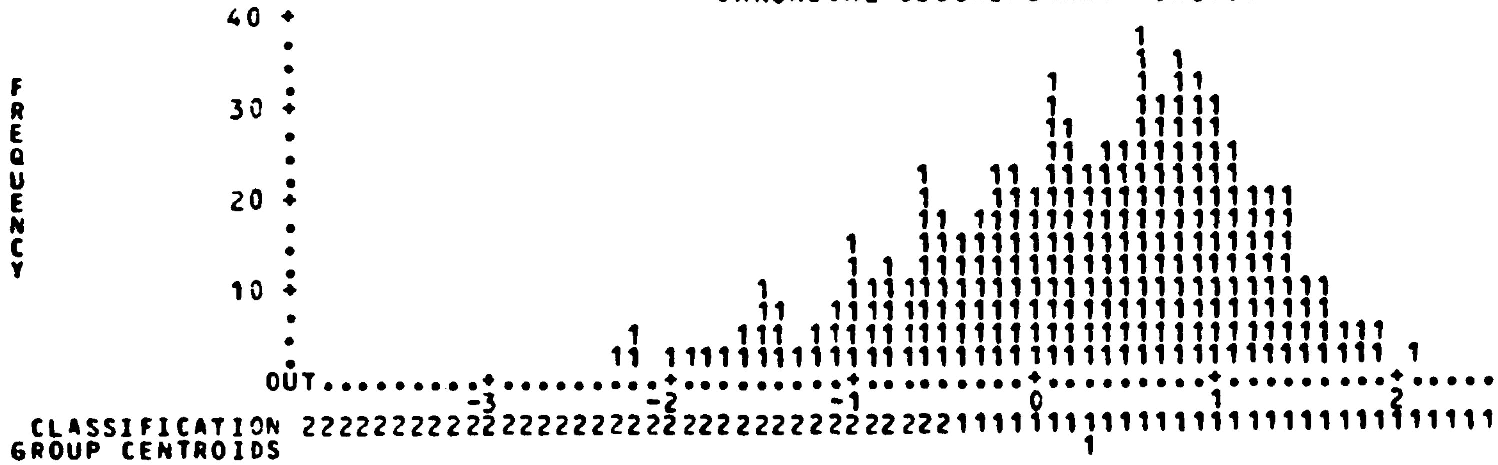


FIGURE 2

WILLIAMS, 2-GROUP DISCRIM.
WILKS-ALL VARS IN-EQUAL

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --

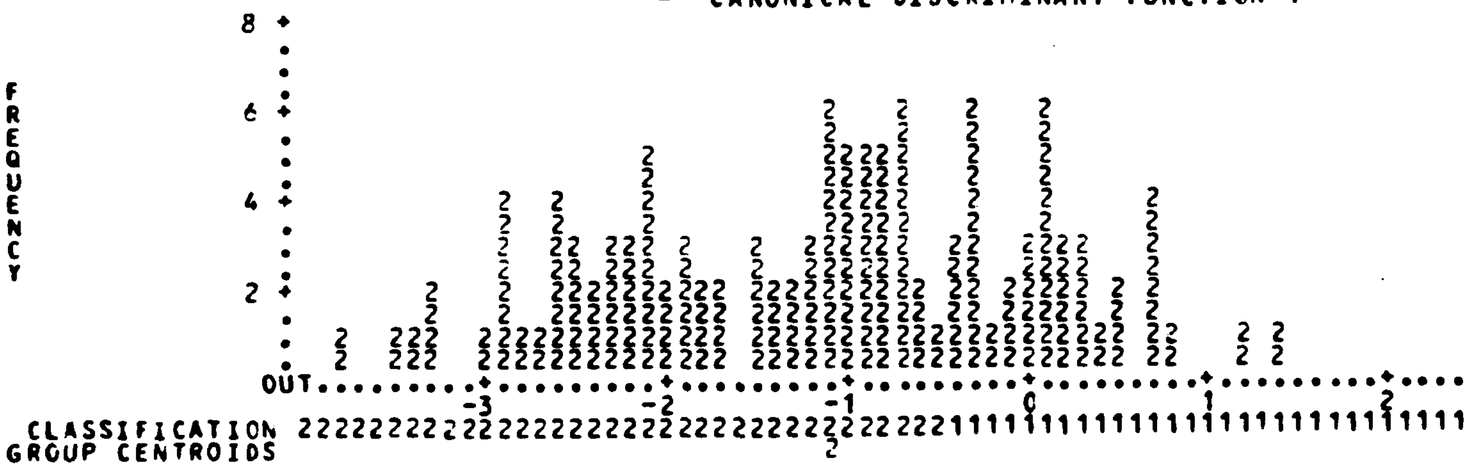
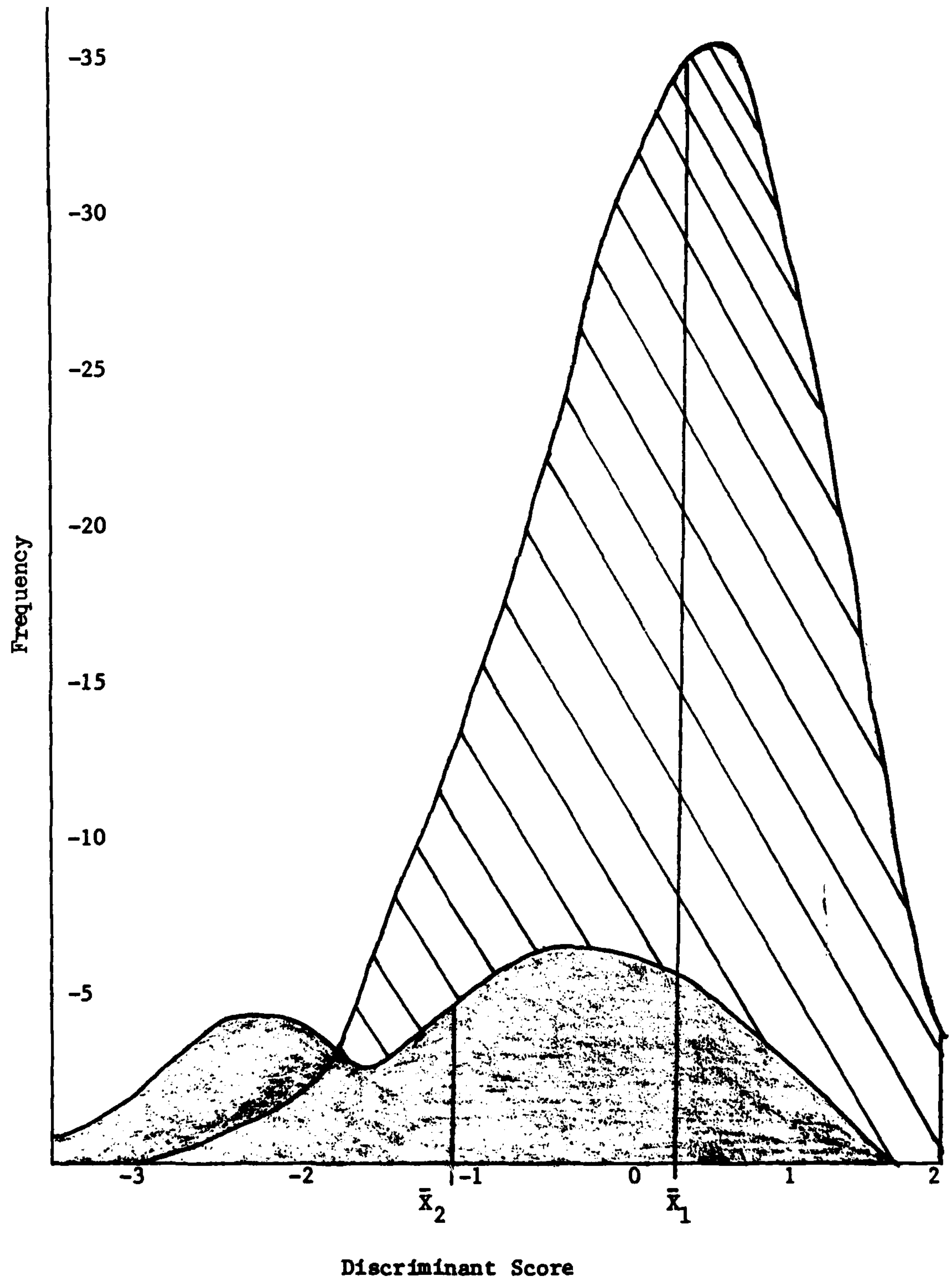


FIGURE 3


-35
-30
-25
-20
-15
-10
-5
Frequency
-3
-2
-1
0
1
2
$\bar{X}_2$
$\bar{X}_1$
Discriminant Score

Classification

The third part of the analyses was to produce classification tables based on the developed classification equations. Classification procedures, as given by SPSS DISCRIMINANT, utilize the pooled within-groups covariance matrix and the centroids for the discriminating variables. Jennrich [1977] and Gondek [1981] discuss the classification derivations and a brief review of their discussion is given in Appendix C. One could conclude from the knowledge of unequal dispersion matrices and the group mean bias, imposed by nonnormality of the group distributions, that it may not be optimal to classify subjects utilizing the SPSS produced classification equations. Overall and Klett [1972] have recommended classification by graphic inspection in such cases, since no theoretical assumptions are necessary. The graphic procedure requires the selection of an appropriate cutting score Y_c and classifies individuals from the discriminant reduced space. The discriminant reduced space refers to the univariate distributions of the standardized discriminant scores, as opposed to the test-space utilized in the packaged classification functions. Those scores greater than the cutting point Y_c are classified into one group and all others into the other group. The choice of Y_c will depend on the acceptable level of misclassification for the two groups. A graphic classification was accomplished from the SPSS produced histograms to assess whether this method would offer improvement in classification.

Under equal *a priori* assumptions, an individual entering the training program has an equal chance of failing or graduating. However, since knowledge of the a priori odds of graduating or failing is known, a Baysian adjustment can be made to the classification equations so that this knowledge can be taken into account. The SPSS procedure is to add the natural log of the prior probabilities to the classification equation constants [Hull and Nie, 1979]. Morrison [1964] offers a method for evaluating the classification tables produced ("confusion matrix") in light of the chance probability of correctly classifying an individual when the population odds of membership are known. The probability of an individual being classified correctly by chance is

$$P(\text{Correct}) = P(\text{Correct/Classified Group I}) \cdot P(\text{Classified Group I}) + P(\text{Correct/Classified Group II})$$

$$P(\text{Correct}) = p \cdot \alpha + (1-p)(1-\alpha)$$

where p = true proportion of Group I and α = proportion classified as Group I. If one is forced to classify to the proportions of each group in the population, then the chance criterion is

$$C_{pro.} = \alpha^2 + (1-\alpha)^2.$$

A maximum chance classification based on classifying everyone into the larger group is given by

$$C_{max.} = (\alpha,\ 1-\alpha), \text{ whichever is greatest.}$$

For this data;

$$C_{pro.} = 74.4\%$$

$$C_{max.} = 85\%$$

Table 9 compares the linear equal and unequal a priori results. Table 10 presents the quadratic classification results and Table 11 is the results of the graphic procedure, where the cutting point Y_c was chosen

TABLE 9. LINEAR CLASSIFICATION WITH EQUAL AND UNEQUAL A PRIORI RESULTS

	Actual Group	Total N	Equal a priori PREDICTED		Unequal a priori PREDICTED		Estimated a priori Probability
			Graduate	Failure	Graduate	Failure	
Development	Graduate	398	312	86	383	15	.83
	Failure	76	25	51 *76.6%	49	27 86.5%	.17
Cross-Validation	Graduate	268	212	56	260	8	.83
	Failure	42	13	29 77.7%	28	14 88.4%	.17

*Total % Correct

such that the misclassifications for each group are held to a minimum ($Y_c = -1.6$). Table 12 compares all the classification results in light of Morrison's chance criterions.

TABLE 10. QUADRATIC CLASSIFICATION RESULTS

Actual Group		N	PREDICTED Graduate	PREDICTED Failure
Development	Graduate	398	337	61
	Failure	76	29	47
				81%
Cross-Validation	Graduate	268	215	53
	Failure	42	18	24
				77.1%

TABLE 11. GRAPHIC CLASSIFICATION RESULTS*

Actual Group	N	PREDICTED Graduate	PREDICTED Failure
Graduate	666	646	20
Failure	118	77	41
			87.6%

*cutting score, $Y_c = -1.6$

It can be seen in Table 12 that all classification rules exceed that which would be expected by chance alone. The linear rule incorporating the population actual a priori odds, and the graphic rule, exceed the

$C_{max.}$ criterion. The quadratic rule, which performed well in the initial classification of the development subsample, performed less satisfactorily than the others on cross-validation. This is consistent with the sensitivity of the rule to nonnormal distributions [Lachenbruch, 1975].

TABLE 12. EFFECTIVENESS OF CLASSIFICATION RESULTS COMPARED TO CHANCE

Classification Rule: a priori	Total Correct Classification	Correct % by Chance	% Correct Graduates	% Correct Failures
Linear-equal	77.7%	66%	94%	34%
Linear-unequal	88.4%	80%	90%	64%
Quadratic-equal	77.1%	68%	92%	31%
Graphic	87.6%	80%	89%	67%

Appendices D-F contain reproductions of the input statements and output produced (discriminant function, classification equations, statistics, etc.) by the SPSS Discriminant procedure for the linear equal and unequal a priori assumptions and quadratic procedure.

Subsidiary Analysis

A separate analysis was run on the data to evaluate the shape and distributions of the discriminant scores when a different sample is selected and the mean replacement of missing values is not incorporated in either the development subsample or cross-validation subsample. This was done to evaluate the effect that mean replacement might have on the shape and means of the group distributions. Figure 4 and Figure 5 show the distributions when only complete data sets are used in all phases of the analysis. It can be seen that a greater negative skew results when mean replacement is avoided in the Graduate group. The distribution of the Failures appears to demonstrate more of a bimodal shape than when mean replacement is used. It is noted that the percent of correct classifications for this procedure was slightly less than that obtained when mean replacement was used.

Appendix G contains the computer input and output for the subsidiary analysis.

FIGURE 4

```
WILLIAMS, 2-GROUP DISCRIM.
SUBSIDIARY ANALYSIS

SYMBOLS USED IN PLOTS

SYMBOL  GROUP  LABEL
------  -----  --------------------

  1       1
  2       2
```

HISTOGRAM FOR GROUP 1

-- CANONICAL DISCRIMINANT FUNCTION 1 --

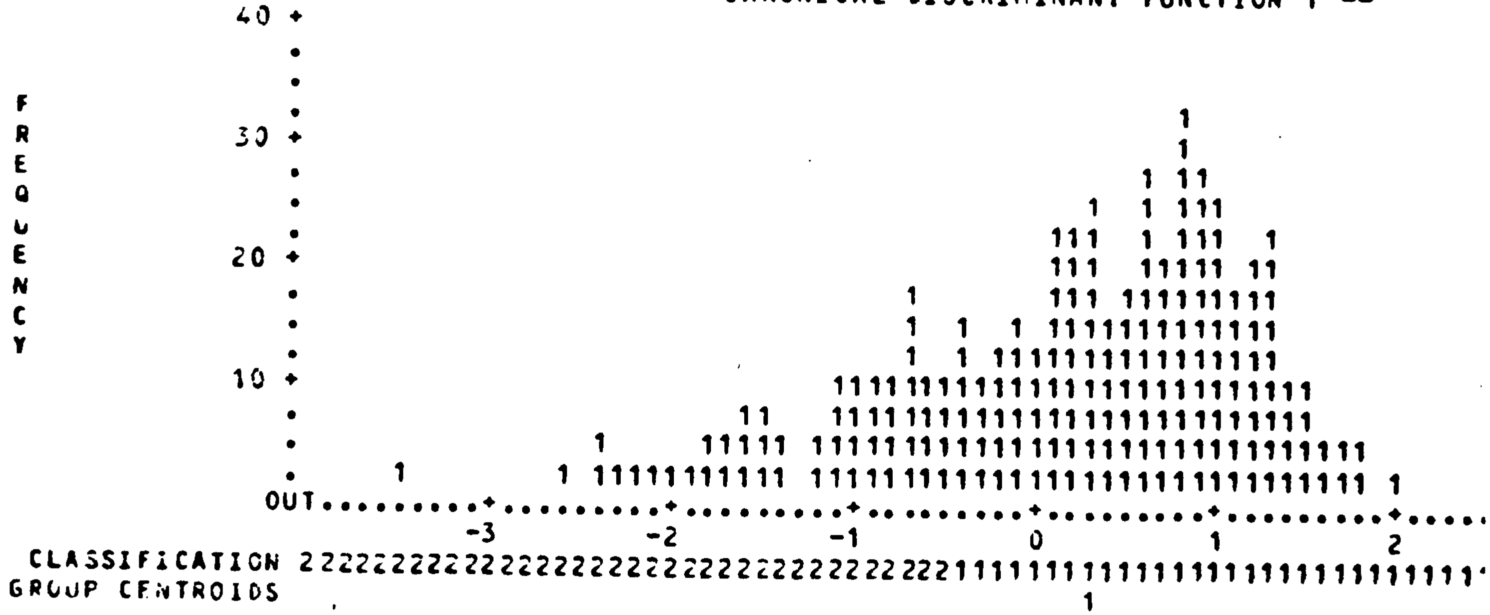
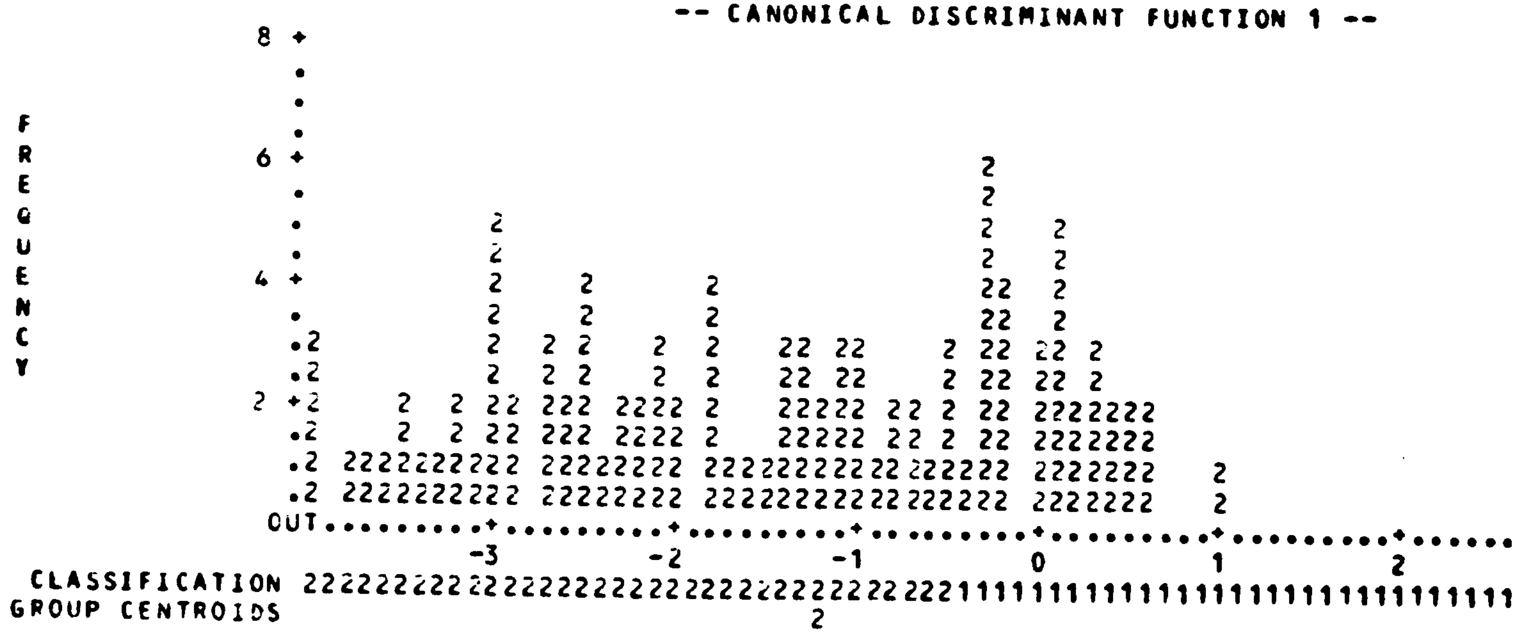


FIGURE 5

```
WILLIAMS, 2-GROUP DISCRIM.
SUBSIDIARY ANALYSIS

SYMBOLS USED IN PLOTS

SYMBOL  GROUP  LABEL
------  -----  ------------------

  1       1
  2       2
```

HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --



DISCUSSION

Summary of Results

Results of this study indicate that numerical ability is the dominant predictive characteristic of success in the USAF Medical Laboratory Specialist courses. This substantiates the findings of Roark [1981] in his study of MLS success and is consistent with the findings of Duteman _et al_. [1966] and those of Driver and Feeley [1974] who studied civilian medical laboratory programs. Mean differences between the groups (Table 1) were most pronounced for the Mathematics Pretest (MPT) and the highest correlation to Graduation was found in the MPT. The aptitude scores, in general, did not appear to be very significant in relation to successful completion of the course. When the MPT is held constant, the highest aptitude test validity is .13 (EL). Thus, it seems that not only is numerical knowledge being incorporated in the MPT, but so are elements of verbal and perceptual aptitudes that are measured by the other composites.

However, two considerations must be taken into account before dismissing the validity of the aptitude composites. First, individuals entering the MLS course are preselected based upon an acceptable score on the General Aptitude Index (GI). Eighty-five percent of the students selected in this manner will, on the average, pass the courses. This alone demonstrates high validity for the GI. Secondly, since explicit preselection has occurred on the variable, its range has been restricted (note that the GI has the lowest standard deviation of all the aptitude composites), and as such, it will have spuriously lower correlations to Graduation [Nunnally, 1978; Guilford and Fruchter, 1978]. It is recommended by many that a correction be made to the correlation of the restricted variable based on the knowledge of the standard deviations of the variable for both the restricted and unrestricted populations [Cronbach, 1960; Gullickson and Hopkins, 1976; Guilford and Fruchter, 1978]. Such corrections assume linearity of regression and homoscedastic variances in the populations. Valentine [1981] has found that these assumptions were not met for the population during this data collection time frame. However, Osburn and Greener [1980], using Monte Carlo techniques, found that under moderate degrees of restriction the corrections are quite robust to nonnormality and deviations from linearity. If independence of the test variables could be assumed, then the corrected correlation for GI would most likely be more accurate then the corresponding uncorrected estimate. This is not the case for the variables in this study. Due to the moderate to high collinearity, it is apparent that the "unrestricted" variables have also been restricted implicitly. To adjust for explicit preselection without making corresponding adjustments to the other variables would make interpretation speculative at best. Thus, a correction is not made. The best that can be said is that the GI validity is less than what would be expected on an unrestricted population and that due to implicit preselection on the other composites, they too would most likely have greater predictive validity.

The moderately high correlations that both the Electronics and General composites have with the AFQT (.77 and .80, respectively) high-light their resemblance to the general intelligence test. This is especially apparent for the General, which is the AFQT minus the spatial perception subtest. It appears, therefore, that the only criterion for admission to MLS technical training is an interest, a quota, and an acceptable general intelligence. As such, the USAF's applied concept of differential validity in occupational prediction, as exemplified by the use of the Armed Services Vocational Aptitude Battery (ASVAB), does not apply to the MLS training program. In light of the various techniques of special attention that course instructors must provide to maintain a low attrition level, i.e., special instruction time, remedial mathematics training programs, retesting and recycling [Hagen, 1981], and the predominance of numerically related task deficiencies reported by supervisors and personnel in the field [Carroll, 1980], some measure of differential selection could be beneficial. Since the MPT offers the most significant validity to graduation, the use of a test of mathematics knowledge in preselection appears warranted. This finding supports the recommendations that were made by Roark [1981a]. The use of such a test, incorporated with the present General composite, would most likely approximate the validity of the MPT (as noted previously, it appears that the MPT is measuring more than just mathematics knowledge). In the unrestricted population, this composite would probably be significantly better than the MPT.

In the second part of the study a discriminant model was developed to assess its utility for discriminating between course Graduates and Failures. It is seen from inspection of the classification tables in Table 9 thru 12, that under appropriate _a priori_ considerations the

LDF can predict with a minimum of misclassifications significantly better than chance. Also, the statistical evidence presented in cross-validation show that the LDF will produce predictions that are reasonably accurate and stable. This is especially encouraging in light of the deviations from theoretical assumptions; however, many researchers have also found this to be true [Gilbert, 1968; Eisenbeis and Avery, 1972; Mark and Dunn, 1974; Pohl, 1974; Lachenbruch, 1975]. The question then becomes: Of what utility is the model?

Probably the most effective uses of the model for course administration would be in the area of counseling and remedial training. Granted, the classification of an individual as a "Failure" could be rather devastating to a person just entering an occupational training program. However, what the discriminant classification of "Failure" means is:

> that based on the test scores and past performances of students in this program, your scores indicate that you look most like those that have failed the course and that your probability of failing is higher than your probability of graduating.

Based on this assessment, appropriate remedial training can be instituted to decrease the probability of failure. The ease of which appropriate cutoff points can be established, either by graphic or generated classification functions using *a priori* information and/or costs of misclassification, makes the model very adaptable to managerial control of a remedial program. As shown in Table 8, the power of the LDF developed in this study appears to be dominated by the MPT. It would be expected that for those cases where failure is predicted, the student most likely demonstrated poor mathematical ability. As such, remedial training in mathematics might be an appropriate strategy.

The most interesting aspect of the LDF, however, was in the descriptive picture obtained by plotting the frequencies of the standardized discriminant scores. The scaled drawing, shown in Figure 3, exhibits the moderate amount of overlap that exists between the two groups and the apparent bimodal form of the Failure group. Inferring from this, it seems that two populations exist: one group that can be discriminated fairly well, and a second, larger group, which seems to have the ability to pass (based on the variables used), and which cannot be discriminated from the Graduates without incurring a large misclassification rate. One explanation that is proposed, is based on the literature dealing with predicting laboratory training success in college. Various studies have shown that the majority of college freshman entering a medical technology curriculum have a general lack of knowledge of the task requirements in the different health fields [Duteman et al., 1966; Youse and Clark, 1977; Gleich, 1978]. Also, Rausch and McClune [1969] found in a study of college freshman, that those leaving medical technology programs showed a greater interest in social service than the medical technology graduates. This may be supported by Duteman et al. [1966] who, when attempting to discriminate between the different allied health care fields, found that medical technology graduates score lower than the other health care fields on a scale of personal interaction. Enlistees entering the USAF and desiring of a health care field may find the clinical laboratory curriculum not meeting their expectations. This may be especially critical for the young enlistee who is entering his/her first job experience. In most cases, recruiters surely examine the cognitive aptitudes of the applicant for assignment purposes and may even handle some noncognitive aspects in a subjective manner. It is most likely that task specifics and the amount and type of patient contact are not discussed. Since academic failures in MLS training are typically reassigned into other health care training programs at the School of Health Care Sciences, where job specific numerical and technical requirements are less than in MLS school, it may be that the student dealing with unmet expectations, finds his/her motivation becoming one of reassignment rather than academic proficiency.

Expectations however, appear to be only one aspect of a growing body of military technical training research supporting the use of noncognitive measures in placement. Guinn et al. [1977], in their study of Security Police training, found that interests were of practical value in prediction of training success. Hoiberg and Pugh [1978] and Webster et al. [1978] found life history items, motivation, expectations, and personality to be factors in persistance in training. Supported by the growing evidence, the inclusion of noncognitive variables into the discriminant function may not only alleviate the bimodal situation but also improve discrimination.

The final objective of this study was to evaluate the use of the LDF in light of the recommendations of Maginnis et al. [1975] for an optimal aptitudes requirements system. A LDF could be very functional in establishing and modifying the aptitude requirements for entry into MLS training. When utilized on an unrestricted population with tests of specific aptitudes, optimal composites to a criterion of Graduation could be obtained. Furthermore, based on manpower requirements, the costs of misclassification could be easily adjusted by one change to the constants of the classification rules or simple adjustment to the cutoff score, thus, allowing more selective or less selective entry with accurate estimates of misclassification.

The Graduate/Failure criterion, plus the inclusion of noncognitive measures into the model, deemphasizes the question of how well can I perform in the training, but does answer the question of what group do I most resemble in the training program. Minimal versus maximal performance in training is not a criterion. This might be appropriate when the findings of Ghiselli [1966] are taken into account; that is, training performance does not necessarily predict proficiency on-the-job. Specific weaknesses are best left to training instructors who can design a program of study to meet the needs of their students and their occupational specialty.

Limitations

Two population effects were encountered during the time frame of the study that need to be addressed. First, in April 1980, the score required for passing course tests was raised from 60% to 70% and the recycling capability of test failures was reduced to maintain favorable student/teacher ratios [Hagen, 1981]. A review of the discriminant scores in the failure group was accomplished to see if increased failures could have affected the shape of the student distributions. The following percentages were found in the smaller mode of the failure distribution; 71% for the five months evaluated in FY78, 36% for FY79, and 23% for FY80. This seems to demonstrate a general trend towards more failures locating in the larger, less discriminating mode. This would be consistent with progressively higher standards being applied to the training pass-criterion and/or lessened ability to perform remedial efforts.

The second limitation deals with the percentile metric norming procedure that was used by the USAF during the period when ASVAB Forms 6/7 were being used. Valentine [1981] noted that beginning with the use of these Forms and up until October 1980, a nonlinear error in normalizing the aptitude scores occurred. This had the effect of increasing reported scores above that which was correct. As such, lower aptitude personnel may have been admitted to some programs where higher standards applied. He also noted a study done by Simm and Truss [1979] that found that the ranking of student aptitudes was not changed. For the study, this effect was held constant by the inclusion of only those personnel that took the ASVAB Forms 6/7. This is based on the assumption of attendence in military basic training for those students evaluated in late November and early December classes of FY80. One by-product of this norming error may have been to increase the frequency of students in the larger mode of the Failure group. Since their aptitude scores are higher than actuality, they would appear to be of higher ability, yet eventually fail. However, it is felt that this bias is not a significant factor in the apparent bimodal distribution. This is due to the fact that the dominant variable in the discriminant function is the MPT. The MPT is given after assignment to the MLS course, thus, not affected by the norming error.

Suggestions for Further Research

The one aspect of the study that seems to require further research is the determination of what factors are responsible for the bimodal distribution in the Failure group. It may be that if appropriate meaures are taken to include mathematical knowledge as a prerequisite to course admission, this shape could change, quite likely in the form of reducing the most easily discriminated mode of the Failure group. The answer to the larger proportion of failures may lie in assessing noncognitive aspects of the individuals entering the program. A longitudinal study spanning both training and on-the-job attrition, using cognitive and noncognitive measures, might be able to define those variables significant to training and retention in the field.

Secondly, based on the literature dealing with aptitudes and interests of laboratory personnel and their apparent differences from other allied health fields, it may be helpful to determine if it is still appropriate to compare MLS technical training requiements to that of the other allied health specialties.

Thirdly, a study of present procedures used by recruitment personnel, when counseling prospective employees on the USAF Medical Laboratory Specialist career field, would offer an assessment of weaknesses in that effort. An approach aimed at defining the task requirements of this career field may not only bring persons interested in a highly technical field into the MLS program, but would also enlighten applicants to the relative independence of this career from that of the other allied health sciences.

Also, a follow-up study using the raw scores obtained by MLS students on each subtest would remove any effects that inaccurate norming might have had and also allow for a direct approach to the assessment of specific subtest validity.

Conclusions

From the preceding data, it has been concluded:

1. The most effective predictor of graduation in courses J3ABR90430, Medical Laboratory Specialist (Phase I) and J5AZ090450, Medical Laboratory Specialist (Phase II) combined, is the course-developed Mathematics Pretest (MPT).
2. The most powerful discriminator between Graduates and Failures in the Linear Discriminant Function developed, is the course-developed Mathematics Pretest;
3. The frequency curve of the discriminant scores for Graduates appears to approach that of the frequency curve of a normal distribution, but does demonstrate a slight negative skew;
4. The frequency curve of the discriminant scores of Failures appears to be bimodal in shape, with approximately 34% of the group in the smaller mode (which is most distant from the Graduate mean);
5. A Linear Discriminant Function utilizing unequal _a priori_ odds of graduating and failing was able to produce a stable, and accurate classification of Graduates and Failures with a minimum of misclassifications on cross-validation;

6. The use of a Linear Discriminant Function is effective for evaluating the importance of specific aptitudes for differentiating Graduates from Failures in training, and is easily modified to take into account differing *a priori* odds of membership and/or differing costs of misclassification.

APPENDIX A

THE ARMED SERVICES VOCATIONAL APTITUDE BATTERY (ASVAB)

APPENDIX A

The Armed Services Vocational Aptitude Battery (ASVAB)

Forms 5, 6, 7

Composites

AFQT..WK + AR + SP

Mechanical Aptitude (MI).......................AI + MC + SI

Administrative Aptitude (GI)...................WK + AD + NO

General Aptitude (GI)..........................WK + AR

Electronics Aptitude (EL)......................AR + SP + EL

Subtests

1. Numerical Operations (NO): measures how rapidly and accurately a subject can complete arithmetic operations, such as addition, subtraction, multiplication and division. Fifty item speeded test with three minute time limit.

2. Attention to Detail (AD): designed to measure the aptitude to perceive simple relationships, to store these relationships mentally, and to decide upon them quickly and accurately. The subject is presented with 30 items, each comprised of two lines of O's with a varied number of C's mixed in, and asked to indicate, for each item, the total number of C's in both lines. Five minute speeded test.

3. Word Knowledge (WK): an index of verbal comprehension that is dependent upon the aptitude to understand written and spoken language. It is a ten minute word comparison test.

4. Arithmatic Reasoning (AR): constructed to measure general reasoning, which is dependent upon the aptitude to solve arithmetic word problems.

5. Space Perception (SP): entails the skill to visualize and manipulate objects in space. Subjects are presented pictorial items, each consisting of flat patterns and four drawings of three dimensional figures. Broken lines indicate where the figure is to be folded. Subject must decide which pattern, when folded, equals the three dimensional figure.

6. Electronics Information (EI): an index of the cognitive aptitude to use acquired electronics relationships, symbols, principles, and diagrams.

7. Mechanical Comprehension (MC): the subject is presented with pictorial items and asked to indicate what they represent. Familiarity with ordinary tools and mechanical relations is a prerequisite.

8. Shop Information (SI): an index of an aptitude that is dependent upon knowledge about and experience with variety of tools found in a shop.

9. Automotive Information (AI): measures aptitude pertaining to diagnosis of automobile malfunction, use of specific automotive parts, operation of automotive components and knowledge of auto terminology.

Forms 8, 9, 10

Composites

AFQT..AR + WK + PC + NO

Mechanical..................................GS + A/SI + MC

Administrative..............................WK + PC + NO + CS

General.....................................AR + WK + PC

Electrical..................................GS + AR + MK + EL

Subtests (other than those already noted)

10. General Science (GS): measures knowledge of physics and biology and reasoning involved to perceive relationships between scientific concepts.

11. Mathematics Knowledge (MK): index of the aptitude to use mathematical relationships involved in solving problems in algebra, geometry, fractions, decimals, and exponents.

12. Coding Speed (CS): evaluates ability to quickly and accurately assign coded numbers by relating them to specific words. Tests clerical aptitude in speeded operations.

Information on subtests taken from:

Frederico, P. A., Landis, D. B. _Discriminating between failures and graduates in a computer-managed course using measures of cognitive styles, abilities, and aptitudes_. NPRDC-TR-79-21. Navy Personnel Research and Development Center, San Diego, Calif., 1979.

Information on composites taken from:

Department of Defense. _ASVAB Recruiter's Guide_. Military Enlistment Processing Command, Ft. Sheridan, Illinois, 1976.

APPENDIX B

LINEAR DISCRIMINANT FUNCTION COMPUTATION

APPENDIX B

Linear Discriminant Function Computation

The solution of the discriminant function problem requires determining the weights to be given to each of the p original variables so that the resulting composite score will have maximum utility for discriminating between the groups. The function is of the form:

$$Y = a_1x_1 + a_2x_2 + \dots\dots\dots + a_px_p \tag{1}$$

where $a_1, a_2, \dots, a_p$ are the weighting coefficients to be applied to the p original scores for each subject. The problem then becomes the determination of optimal weighting values such that the distance between the mean scores for the two groups is maximized relative to the variation within groups. The function to be maximized as defined by R. A. Fisher [1936] is the ratio of between-groups variance to the within-groups variance. In matrix notation this is

$$f(a_i) = \frac{n_1n_2}{n_1 + n_2} \; \frac{a'dd'a}{a'Ca} \tag{2}$$

where $d' = [d_1\ d_2\ \dots\ d_p]$ is the vector of mean differences on the p original variables and C is the within-groups covariance matrix. Maximizing $f(a_i)$ yields a set of equations that can be solved in matrix notation by:

$$Ca = d \tag{3}$$

Premultiplication of both sides by C^{-1} yields the equation from which vector a can be obtained:

$$a = C^{-1}d \tag{4}$$

The mean values for the discriminant function can be obtained by:

$$\bar{Y}^{(1)} = a_1\bar{x}_1^{(1)} + a_2\bar{x}_2^{(1)} + \ldots\ldots + a_p\bar{x}_p^{(1)} \tag{5}$$

$$\bar{Y}^{(2)} = a_1\bar{x}_1^{(2)} + a_2\bar{x}_2^{(2)} + \ldots\ldots + a_p\bar{x}_p^{(2)} \tag{6}$$

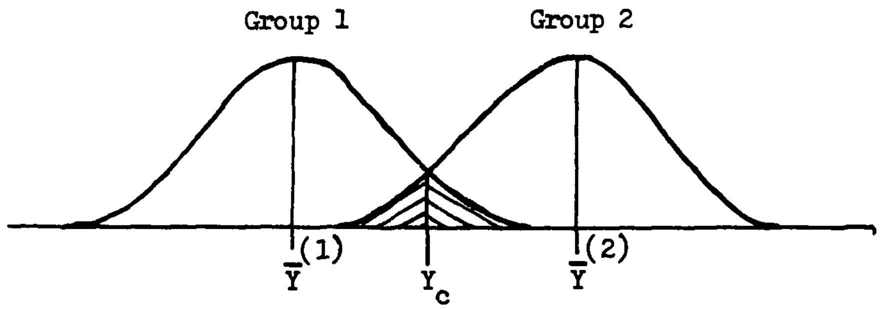
with variance:

$$V(Y) = a'Ca = a'CC^{-1}Ca = d'C^{-1}d. \tag{7}$$

With the assumption of multivariate normal distribution within groups, the discriminant function scores can be seen to have a normal distribution within-groups, with mean values $\bar{Y}^{(1)}$ and $\bar{Y}^{(2)}$ and standard deviation $\sigma = \sqrt{d'a}$. As such the deviation of an individual score from each of the groups can be reguardèd as a unit-normal deviate of Z score:

$$Z_Y = \frac{Y - \bar{Y}^{(i)}}{V(Y)} \tag{8}$$

where $i = 1,2$. Thus for any particular discriminant function score, say Y_c, the Z-scores deviation from each group can be computed. For example:



The discriminant function score Y_c can be accepted as a cutting point for classifying individuals into the two groups. By converting the discriminant score Y_c to Z-score by Eq. (8) and referring to the unit-normal distribution tables, the proportion of misclassifications can be obtained for each group.

Information taken from:

Overall, J. E., Klett, J. C. Applied multivariate analysis. New York: McGraw-Hill, 1972.

APPENDIX C

SPSS CLASSIFICATION FUNCTIONS

APPENDIX C

SPSS Classification Functions

The SPSS classification functions are based on posterior probabilities, that is, probabilities that the individual belongs to each of the given groups, given the subject's values on each of the discriminating variables. The classification functions are of the form:

$$d_i(x) = (X - \tfrac{1}{2}\, \bar{x}^{(i)})' \, \Sigma^{-1} \, (\bar{x}^{(i)})$$

where $X' = (x_1, x_2, \ldots, x_p)$, $\Sigma = S$ = sample pooled within-groups covariance matrix, and $i = 1,2$. Thus two classification functions are produced in the two-group case. Given a random vector $Z' = (Z_{i1}, Z_{i2}, \ldots, Z_{ip})$ that came with equal probability from each of q normal populations with mean vectors $\mu_1, \mu_2, \ldots, \mu_q$, and common covariance matrix Σ, the posterior probability that Z is from the g^{th} population is given by:

$$P(g/Z) = k \, \{\exp[-\tfrac{1}{2}(Z-\mu_g)' \, \Sigma^{-1} \, (Z-\mu_g)]\}.$$

Replacing parameters with sample estimates and choosing k (constant) so that the sum over all q groups of $P(g/Z) = 1$ gives:

$$P(g/Z) = \exp(dg(Z)) / \sum_{q=1}^{q} \exp(dg(Z)).$$

The function d_i which has the largest value at Z corresponds to the group with the greatest (estimated) posterior probability given Z. The new case will be classified in the group corresponding to the largest $P(i/Z)$.

In the case of <u>a priori</u> probabilities, the natural log of the <u>a priori</u> probability is added to the appropriate group constants.

Information taken from:

Gondek, Paul C. What you see may not be what you think you get: discriminant analysis in statistical packages. Educational and Psychological Measurement, 1981, 41 (2), 267-281

Hull, H.C., Nie, N. H. SPSS update: new procedures and facilities for releases 7 and 8. New York: McGraw-Hill, 1979.

APPENDIX D

LINEAR EQUAL *A PRIORI* CLASSIFICATION

```
SPSS BATCH SYSTEM                                                      11/18/81        PAGE    1

SPSS FOR SPERRY UNIVAC 1100 EXEC 8, VERSION H, RELEASE 8.1-UW1.0, OCTOBER 1980

             1.  ALLOCATE         SPACE=49000/TRANSPACE=1800

SPACE ALLOCATION..             ALLOWS FOR..     60 TRANSFORMATIONS
WORKSPACE      47200 WORDS                     240 RECODE VALUES + LAG VARIABLES
TRANSPACE       1800 WORDS                     480 IF/COMPUTE OPERATIONS

             2.  RUN NAME         WILLIAMS, 2-GROUP DISCRIM.
             3.  VARIABLE LIST    DATE,V1,V2,STUDY,V3,V4,V5,V6,V7,V8,V9,V10,MT,BK,FII,ACC
             4.  INPUT FORMAT     FIXED(3F1.0,X,F1.0,X,F2.0,X,F2.0,X,7F3.0,X,2F1.0,F3.0)

                 ACCORDING TO YOUR INPUT FORMAT, VARIABLES ARE TO BE READ AS FOLLOWS

                 VARIABLE  FORMAT  RECORD    COLUMNS

                 DATE      F 1. 0       1      1-  1
                 V1        F 1. 0       1      2-  2
                 V2        F 1. 0       1      3-  3
                 STUDY     F 1. 0       1      5-  5
                 V3        F 2. 0       1      7-  8
                 V4        F 2. 0       1     10- 11
                 V5        F 3. 0       1     13- 15
                 V6        F 3. 0       1     16- 18
                 V7        F 3. 0       1     19- 21
                 V8        F 3. 0       1     22- 24
                 V9        F 3. 0       1     25- 27
                 V10       F 3. 0       1     28- 30
                 MT        F 3. 0       1     31- 33
                 BK        F 1. 0       1     35- 35
                 FII       F 1. 0       1     36- 36
                 ACC       F 3. 0       1     37- 39

THE INPUT FORMAT PROVIDES FOR  16 VARIABLES.   16 WILL BE READ
IT PROVIDES FOR  1 RECORDS ("CARDS") PER CASE.  A MAXIMUM OF   39 "COLUMNS" ARE USED ON A RECORD.

             5.  INPUT MEDIUM     CARD
             6.  N OF CASES       UNKNOWN
             7.  DO REPEAT        X=V1,V1,V1,V1,V1,V1,V1,V1,V1,V1
             8.                     V2,V2,V2,V2,V2,V2,V2,V2,V2
             9.                     V3,V3,V3,V3,V3,V3,V3,V3
            10.                     V4,V4,V4,V4,V4,V4,V4
            11.                     V5,V5,V5,V5,V5,V5
            12.                     V6,V6,V6,V6,V6
            13.                     V7,V7,V7,V7
            14.                     V8,V8,V8
            15.                     V9,V9
            16.                     V10/
            17.                   Y=V1,V2,V3,V4,V5,V6,V7,V8,V9,V10
            18.                      V2,V3,V4,V5,V6,V7,V8,V9,V10
            19.                       V3,V4,V5,V6,V7,V8,V9,V10
            20.                        V4,V5,V6,V7,V8,V9,V10
            21.                         V5,V6,V7,V8,V9,V10
            22.                          V6,V7,V8,V9,V10
            23.                           V7,V8,V9,V10
            24.                            V8,V9,V10
            25.                             V9,V10
```

```
          26.                                    Y10/
          27.                      Z=Z1 TO Z55/
          28.   COMPUTE            Z=X*Y
          29.   END REPEAT

          30.   IF                 ((STUDY EQ 1 OR STUDY EQ 2) AND FII NE 1)GPS=1
          31.   IF                 (STUDY EQ 3 OR STUDY EQ 4 OR FII EQ 1)GPS=2
          32.   IF                 (SEQNUM LE 474)SET=0
          33.   IF                 (SEQNUM GT 474)SET=1
          34.   MISSING VALUES     ALL(-1)
          35.   READ INPUT DATA

@ADD,P WILL*AFDATA.

AFTER READING    784 CASES FROM SUBFILE NONAME  ,  END OF DATA WAS ENCOUNTERED ON LOGICAL UNIT # 5
```

```
TRANSPACE REQUIRED..     1770 WORDS
      59 TRANSFORMATIONS
       0 RECODE VALUES + LAG VARIABLES
     201 IF/COMPUTE OPERATIONS

              36.  TASK NAME        WILKS-ALL VARS IN-EQUAL
              37.  DISCRIMINANT     GROUPS=GPS(1,2)/
              38.                   VARIABLES=V1,V2,V3,V4,V5,V6,V7,V8,V9,V10/
              39.                   SELECT=SET(0)/
              40.                   ANALYSIS=V1 TO V10(1)/
              41.                   METHOD=WILKS/FIN=0.0/FOUT=0.0/
              42.  OPTIONS          2,5,7,8,9,10,11,12
              43.  STATISTICS       1,2,3,4,5,6,7,8,9

THIS DISCRIMINANT ANALYSIS REQUIRES      956 WORDS OF WORKSPACE.
```

WILKS-ALL VARS IN-EQUAL
FILE NONAME (CREATION DATE = 11/18/81)

- D I S C R I M I N A N T   A N A L Y S I S -

ON GROUPS DEFINED BY GPS

784 (UNWEIGHTED) CASES WERE PROCESSED.
398 OF THESE WERE EXCLUDED FROM THE ANALYSIS.
0 HAD MISSING OR OUT-OF-RANGE GROUP CODES.
143 HAD AT LEAST ONE MISSING DISCRIMINATING VARIABLE.
0 HAD BOTH.
255 WERE EXCLUDED BY THE SELECT= VARIABLE.
386 (UNWEIGHTED) CASES WILL BE USED IN THE ANALYSIS.

NUMBER OF CASES BY GROUP

GPS	NUMBER OF CASES UNWEIGHTED	WEIGHTED	LABEL
1	322	322.0	
2	64	64.0	
TOTAL	386	386.0	

GROUP MEANS

GPS	V1	V2	V3	V4	V5	V6	V7	V8
1	.52174	.44099	20.52174	12.80124	85.36957	70.79193	55.79193	75.13975
2	.46875	.51563	19.92188	12.48437	67.09375	57.93750	41.09375	65.00000
TOTAL	.51295	.45337	20.42228	12.74870	82.33938	68.66062	53.35492	73.45855

GPS	V9	V10
1	81.50621	71.58385
2	72.50000	54.06250
TOTAL	80.01295	68.67876

AD-A116 775 AIR FORCE INST OF TECH WRIGHT-PATTERSON AFB OH F/G 5/9
DISCRIMINATING BETWEEN GRADUATES AND FAILURE IN THE USAF MEDICA--ETC(U)
DEC 81 M D WILLIAMS
UNCLASSIFIED AFIT/NR/81-72T NL

2 of 2

END
DATE
FILMED
8-82
DTIC

WILLIAMS, 2-GROUP DISCRIM.
WILKS-ALL VARS IN-EQUAL

GROUP STANDARD DEVIATIONS

GPS	V1	V2	V3	V4	V5	V6	V7	V8
1	.50030	.49728	2.78869	1.18831	13.19176	14.93361	25.23862	16.92191
2	.50297	.50371	2.31835	.90838	19.05357	9.10412	18.54785	18.49496
TOTAL	.50048	.49847	2.72276	1.15165	15.83720	14.91365	24.84656	17.57787

GPS	V9	V10
1	11.68039	18.74092
2	10.19648	18.49228
TOTAL	11.91691	19.78299

POOLED WITHIN-GROUPS COVARIANCE MATRIX WITH 384 DEGREES OF FREEDOM

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2507430+000							
V2	-.2332180+000	.2483418+000						
V3	.1482181-001	.2732075-001	.7382701+001					
V4	-.8176942-002	.1364392-001	.1838055+001	.1315791+001				
V5	.2890767-001	.2194789-001	-.2983381+001	.4967342+000	.2050324+003			
V6	.1558113+000	.5887782-001	.2616260+001	-.3942168+000	.8691181+002	.2000229+003		
V7	.1800626+000	.1470126+000	.1347462+001	-.8938099+000	.1142167+003	.1851756+003	.5889232+003	
V8	.7461504+000	-.3120956+000	-.1858016+001	.1859229+001	.9017805+002	.6355303+002	.6455563+002	.2954916+003
V9	.4415761-001	.8754691-001	.7537935+000	-.6929752+000	.6734573+002	.1250805+003	.1150154+003	.6981047+002
V10	.2266616+000	-.1145035+000	-.2267642+001	-.1730654+001	.1235863+003	.2034567+003	.2961243+003	.5254877+002

	V9	V10
V9	.1311056+003	
V10	.1140803+003	.3497031+003

WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 6
WILKS-ALL VARS IN-EQUAL

POOLED WITHIN-GROUPS CORRELATION MATRIX

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
V1	1.00000									
V2	-.93459	1.00000								
V3	.01089	.02018	1.00000							
V4	-.01424	.02387	.58974	1.00000						
V5	.00403	.00308	-.07668	.03024	1.00000					
V6	.02200	.00835	.06808	-.02430	.42917	1.00000				
V7	.01482	.01216	.12044	-.03211	.32869	.53953	1.00000			
V8	.08666	-.03643	-.03978	.05429	.36637	.26141	.15475	1.00000		
V9	.00770	.01534	.02423	-.05276	.41076	.77239	.43392	.35468	1.00000	
V10	.02421	-.01229	-.04463	-.08068	.46154	.76928	.65252	.16347	.53278	1.00000

CORRELATIONS WHICH CANNOT BE COMPUTED ARE PRINTED AS 99.0.

WILKS' LAMBDA (U-STATISTIC) AND UNIVARIATE F-RATIO
WITH 1 AND 384 DEGREES OF FREEDOM

VARIABLE	WILKS' LAMBDA	F	SIGNIFICANCE
V1	.99845	.5979+000	.4399
V2	.99689	.1197+001	.2745
V3	.99327	.2602+001	.1075
V4	.98950	.4074+001	.0442
V5	.81534	.8697+002	.0000
V6	.89698	.4410+002	.0000
V7	.95147	.1958+002	.0000
V8	.95386	.1858+002	.0000
V9	.92080	.3303+002	.0000
V10	.89122	.4687+002	.0000

COVARIANCE MATRIX FOR GROUP 1.

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2503048+000							
V2	-.2308005+000	.2472862+000						
V3	.3535148-001	.5959637-002	.7776785+001					
V4	-.1896248-002	.6927111-002	.1994988+001	.1412086+001				
V5	-.2708926-003	.1013138+000	-.1355411+001	.5752404+000	.1740219+003			
V6	.1774366+000	.1013912+000	.1987407+001	-.6489619+000	.9824848+002	.2230126+003		
V7	.4578085+000	-.6994834-001	.1176319+001	-.7299588+000	.1246105+003	.2112401+003	.6369877+003	
V8	.7524062+000	-.2175848+000	-.2756332+000	.1912598+001	.8158371+002	.7224101+002	.7449957+002	.2863511+003
V9	.3724773-001	.1592461+000	.8733692+000	-.7121573+000	.7319552+002	.1386321+003	.1335387+003	.7829352+002
V10	.4639036+000	-.2956599+000	-.3305567+001	-.2082971+001	.1224970+003	.2215300+003	.3179786+003	.5912376+002

	V9	V10
V9	.1364314+003	
V10	.1310961+003	.3512219+003

COVARIANCE MATRIX FOR GROUP 2.

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2529762+000							
V2	-.2455357+000	.2537202+000						
V3	-.8978175-001	.1361607+000	.5374752+001					
V4	-.4017857-001	.4786706-001	.1038442+001	.8251488+000				
V5	.1775794+000	-.3824405+000	-.1127827+002	.9672619-001	.3630387+003			
V6	.4563492-001	-.1577381+000	.5820437+001	.9037698+000	.2914881+002	.8288492+002		
V7	-.1235119+001	.1252480+001	.2229663+001	-.1728671+001	.6227679+002	.5237103+002	.3440228+003	
V8	.7142857+000	-.2936508+000	-.9920635+001	.1587302+001	.1339683+003	.1928571+002	.1388889+002	.3420635+003
V9	.7936508-001	-.2777778+000	.1190476+000	-.5952381+000	.3753968+002	.5603175+002	.2063492+002	.2658730+002
V10	-.7821429+000	.8085317+000	.3020833+001	.6448413-001	.1291369+003	.1113690+003	.1847718+003	.1904762+002

	V9	V10
V9	.1039683+003	
V10	.2738095+002	.3419643+003

TOTAL COVARIANCE MATRIX WITH 385 DEGREES OF FREEDOM

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2504811+003							
V2	-.2331606+000	.2484691+000						
V3	.1919117-001	.2104165-001	.7413424+001					
V4	-.5827333-002	.1032905-001	.1859639+001	.1326297+001				
V5	.1631250+000	-.1672498+000	-.1455373+001	.1298493+001	.2508170+003			
V6	.2498621+000	-.7430859-001	.3678755+001	.1716372+000	.1192635+003	.2224170+003		
V7	.2875986+000	-.5484153-002	.2566617+001	-.2456430+000	.1511701+003	.2108948+003	.6173516+003	
V8	.3187201+000	-.4162257+000	-.1009723+001	.2299946+001	.1156414+003	.8146252+002	.8505501+002	.3089814+003
V9	.1102216+300	-.5887894-002	.1501005+001	-.2954377+000	.8999559+002	.1408096+003	.1330733+003	.8229275+002
V10	.3548213+000	-.2955387+000	-.8042527+000	-.9562614+000	.1676703+003	.2341608+003	.3310676+003	.7704899+002

	V9	V10
V9	.1620128+203	
V10	.1356665+003	.3913667+003

- D I S C R I M I N A N T   A N A L Y S I S -

ON GROUPS DEFINED BY GPS

ANALYSIS NUMBER   1

STEPWISE VARIABLE SELECTION

SELECTION RULE: MINIMIZE WILKS' LAMBDA
MAXIMUM NUMBER OF STEPS.................... 20
MINIMUM TOLERANCE LEVEL.................... .00100
MINIMUM F TO ENTER......................... .00000
MAXIMUM F TO REMOVE........................ .00000

CANONICAL DISCRIMINANT FUNCTIONS

MAXIMUM NUMBER OF FUNCTIONS................ 1
MINIMUM CUMULATIVE PERCENT OF VARIANCE..... 100.00
MAXIMUM SIGNIFICANCE OF WILKS' LAMBDA...... 1.0000

PRIOR PROBABILITY FOR EACH GROUP IS .50000

------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 0 -------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	1.0000000	1.0000000	.59785+000	.9984655
V2	1.0000000	1.0000000	.11974+001	.9968915
V3	1.0000000	1.0000000	.26022+001	.9932691
V4	1.0000000	1.0000000	.40740+001	.9895021
V5	1.0000000	1.0000000	.86972+002	.9153351
V6	1.0000000	1.0000000	.44104+002	.8969791
V7	1.0000000	1.0000000	.19585+002	.9514732
V8	1.0000000	1.0000000	.16576+002	.9538565
V9	1.0000000	1.0000000	.33030+002	.9207965
V10	1.0000000	1.0000000	.46869+002	.8912225

* *

AT STEP 1, V5 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.8153351	1	1	384.0		
EQUIVALENT F	.8697200+002		1	384.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 1 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V5	1.0000000	.86972+002	

-------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 1 --------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	.9999837	.9999837	.44005+000	.8143994
V2	.9999905	.9999905	.10255+001	.8131579
V3	.9961200	.9961200	.44343+001	.8060033
V4	.9990854	.9990854	.24560+001	.8101441
V6	.8158146	.8158146	.69604+001	.8008232
V7	.8919617	.8919617	.16866+001	.8117606
V8	.8657748	.8657748	.74957+000	.8137425
V9	.8312760	.8312760	.35931+001	.8077571
V10	.7869808	.7869808	.66762+001	.8013663

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 1
EACH F STATISTIC HAS 1 AND 384.0 DEGREES OF FREEDOM.

GROUP	1
2	86.972 .0000

* *

AT STEP 2, V6 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.8008232	2	1	384.0		
EQUIVALENT F	.4762894+002		2	383.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 2 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V5	.8138146	.45987+002	.8969791
V6	.8138146	.69404+001	.8153351

------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 2 -------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	.9994801	.8134037	.35785+000	.8000737
V2	.9999299	.8137651	.10458+001	.7986368
V3	.9816180	.8045475	.32515+001	.7940643
V4	.9973819	.8161595	.27542+001	.7950905
V7	.6973414	.6378091	.58109-002	.8008110
V8	.9524715	.7464692	.28927+000	.8002172
V9	.3957032	.3883432	.26950-003	.8008226
V10	.3870528	.3870528	.99226+000	.7987484

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 2
EACH F STATISTIC HAS 2 AND 383.0 DEGREES OF FREEDOM.

GROUP	1
2	47.629 .0000

* *

AT STEP 3, V3 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7940643	3	1	384.0		
EQUIVALENT F	.3302312+002		3	382.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 3 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V3	.9816180	.32515+001	.8008232
V5	.8045475	.48149+002	.8941507
V6	.8055550	.57435+001	.8060033

-------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 3 --------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	.9994031	.8045281	.33545+000	.7933658
V2	.9995408	.8045451	.11079+001	.7917621
V4	.6347006	.6246690	.50889+000	.7930051
V7	.6973276	.6312585	.70224-002	.7940497
V8	.8518559	.7382675	.34020+000	.7933559
V9	.3953706	.3845825	.12725-002	.7940616
V10	.3805416	.3805416	.15218+001	.7909052

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 3
EACH F STATISTIC HAS 3 AND 382.0 DEGREES OF FREEDOM.

GROUP	1
2	33.023 .0000

* *

AT STEP 4, V10 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7909052	4	1	384.0		
EQUIVALENT F	.2518162+002		4	381.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 4 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V3	.9651046	.37783+001	.7987486
V5	.7677884	.41293+002	.8766232
V6	.3895656	.58464+000	.7921189
V10	.3805416	.15218+001	.7940643

-------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 4 --------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	.9991968	.3804630	.31322+000	.7902539
V2	.9987778	.3802511	.10312+001	.7887648
V4	.6336556	.3799150	.57992+000	.7897001
V7	.5683658	.3101653	.24321+000	.7903994
V8	.8347992	.3729220	.58217+000	.7896954
V9	.3803355	.2185287	.78800-001	.7907413

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 4
EACH F STATISTIC HAS 4 AND 381.0 DEGREES OF FREEDOM.

GROUP	1
2	25.182
	.0000

* *

AT STEP 5, V2 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7887648	5	1	384.0		
EQUIVALENT F	.2075319+002	5		380.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 5 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V2	.9987778	.10312+001	.7909052
V3	.3648581	.38211+001	.7966962
V5	.7677438	.41174+002	.9742290
V6	.3893467	.61851+000	.7900486
V10	.3802511	.14440+001	.7917621

------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 5 -------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V1	.1267316	.1246793	.12140+001	.7862463
V4	.6335271	.3796374	.59906+000	.7875200
V7	.5680520	.3097644	.21919+000	.7883088
V8	.8330685	.3724955	.51207+000	.7877005
V9	.3803005	.2185003	.83922-001	.7885901

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 5
EACH F STATISTIC HAS 5 AND 380.0 DEGREES OF FREEDOM.

GROUP	1
2	20.353 .0000

* *

AT STEP 6, V1 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7862463	6	1	384.0		
EQUIVALENT F	.1717288+002		6	379.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 6 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V1	.1247316	.12140+001	.7887648
V2	.1246793	.19318+001	.7902539
V3	.9598511	.40983+001	.7947482
V5	.7677606	.40885+002	.8710643
V6	.3871399	.74819+000	.7877984
V10	.3798498	.13493+001	.7890454

-------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 6 --------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V4	.6330576	.1246271	.55070+000	.7851025
V7	.5662607	.1242136	.16437+000	.7859065
V8	.8162643	.1222126	.77184+000	.7846641
V9	.3802867	.1246786	.79655-001	.7860806

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 6
EACH F STATISTIC HAS 6 AND 379.0 DEGREES OF FREEDOM.

GROUP	1
2	17.173 .0000

* *

AT STEP 7, V8 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7846441	7	1	384.0		
EQUIVALENT F	.1482101+002		7	378.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 7 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V1	.1222126	.14724+001	.7877005
V2	.1229660	.21926+001	.7891955
V3	.9569074	.42681+001	.7935037
V5	.6921120	.32609+002	.8523329
V6	.3744735	.47550+000	.7856311
V8	.8162443	.77184+000	.7862463
V10	.3724419	.16148+001	.7879961

-------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 7 --------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V4	.6203176	.1219362	.38727+000	.7838389
V7	.5654459	.1218993	.19151+000	.7842457
V9	.3848276	.1220601	.11460-001	.7846202

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 7
EACH F STATISTIC HAS 7 AND 378.0 DEGREES OF FREEDOM.

	GROUP 1
GROUP	
2	14.821 .0000

* *

AT STEP 8, V4 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7878389	8	1	384.0		
EQUIVALENT F	.1299577+002		8	377.0	.0000	

---------------- VARIABLES IN THE ANALYSIS AFTER STEP 8 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V1	.1219362	.13926+001	.7867363
V2	.1227949	.21130+001	.7882320
V3	.6069462	.15867+001	.7871178
V4	.6233176	.38727+000	.7846441
V5	.6853681	.31362+002	.8490445
V6	.3715130	.54906+000	.7849805
V8	.7998181	.60773+000	.7851025
V10	.3722764	.16418+001	.7872524

------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP 8 -------------------

VARIABLE	TOLERANCE	MINIMUM TOLERANCE	F TO ENTER	WILKS' LAMBDA
V7	.5651960	.1216366	.17965+000	.7834646
V9	.3615476	.1217415	.27723-001	.7837811

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 8
EACH F STATISTIC HAS 8 AND 377.0 DEGREES OF FREEDOM.

GROUP	1
GROUP	
2	12.996 .0000

```
WILLIAMS, 2-GROUP DISCRIM.                                              11/18/81        PAGE   18
WILKS-ALL VARS IN-EQUAL

* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

AT STEP   9, V7       WAS INCLUDED IN THE ANALYSIS.

                                       DEGREES OF FREEDOM  SIGNIFICANCE      BETWEEN GROUPS
WILKS' LAMBDA          .7834646          9    1    384.0
EQUIVALENT F           .1154662+002           9    376.0       .0000

---------------- VARIABLES IN THE ANALYSIS AFTER STEP   9 ----------------

VARIABLE    TOLERANCE    F TO REMOVE     WILKS' LAMBDA

V1          .1216366     .13335+001      .7862474
V2          .1224159     .20316+001      .7876577
V3          .6050441     .16372+001      .7868760
V4          .6200434     .37488+000      .7842457
V5          .6849594     .31373+002      .[illegible]8353
V6          .7706658     .57648+000      .7846658
V7          .5651960     .17965+000      .7838789
V8          .7985338     .63162+000      .7847207
V10         .3026327     .17887+001      .7871516

------------------- VARIABLES NOT IN THE ANALYSIS AFTER STEP   9 -------------------

                          MINIMUM
VARIABLE    TOLERANCE    TOLERANCE     F TO ENTER     WILKS' LAMBDA

V9          .3602231     .1214116      .36943-001     .7833874

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP   9
EACH F STATISTIC HAS   9 AND     376.0 DEGREES OF FREEDOM.

                GROUP        1

   GROUP

      2                   11.547
                           .0000
```

* *

AT STEP 10, V9 WAS INCLUDED IN THE ANALYSIS.

		DEGREES OF FREEDOM			SIGNIFICANCE	BETWEEN GROUPS
WILKS' LAMBDA	.7833874	10	1	384.0		
EQUIVALENT F	.1036904+002	10		375.0	.0000	

--------------- VARIABLES IN THE ANALYSIS AFTER STEP 10 ----------------

VARIABLE	TOLERANCE	F TO REMOVE	WILKS' LAMBDA
V1	.1216116	.13103+001	.7861246
V2	.1222792	.20053+001	.7875765
V3	.6048317	.16229+001	.7867777
V4	.6145981	.39285+000	.7842081
V5	.6760015	.30569+002	.8472470
V6	.2176862	.20909+000	.7838262
V7	.5631256	.18847+000	.7837811
V8	.7629396	.54031+000	.7845161
V9	.3602231	.36963-001	.7834646
V10	.2927131	.18183+001	.7871858

F STATISTICS AND SIGNIFICANCES BETWEEN PAIRS OF GROUPS AFTER STEP 10
EACH F STATISTIC HAS 10 AND 375.0 DEGREES OF FREEDOM.

GROUP	1
2	10.369 .0000

F LEVEL OR TOLERANCE OR VIN INSUFFICIENT FOR FURTHER COMPUTATION.

SUMMARY TABLE

STEP	ACTION ENTERED	ACTION REMOVED	VARS IN	WILKS' LAMBDA	SIG.	LABEL
1	V5		1	.815335	.0000	
2	V6		2	.800623	.0000	
3	V3		3	.794264	.0000	
4	V10		4	.790905	.0000	
5	V2		5	.788765	.0000	
6	V1		6	.786246	.0000	
7	V8		7	.784644	.0000	
8	V4		8	.783839	.0000	
9	V7		9	.783465	.0000	
10	V9		10	.783387	.0000	

CLASSIFICATION FUNCTION COEFFICIENTS
(FISHER'S LINEAR DISCRIMINANT FUNCTIONS)

GPS =	1	2
V1	.2711767+002	.2814262+002
V2	.2654923+002	.2781737+002
V3	.5005431+000	.5064149+000
V4	.9404474+001	.9295472+001
V5	.2357064+000	.1650460+000
V6	-.3801171+000	-.3909571+000
V7	-.8695951-001	-.8323030-001
V8	-.3965961-001	-.4711615-001
V9	.8065858+000	.8022096+000
V10	.1998963+000	.1760921+000
(CONSTANT)	-.1116755+003	-.1014261+003

CANONICAL DISCRIMINANT FUNCTIONS

FUNCTION	EIGENVALUE	PERCENT OF VARIANCE	CUMULATIVE PERCENT	CANONICAL CORRELATION	:	AFTER FUNCTION	WILKS' LAMBDA	CHI-SQUARED	D.F.	SIGNIFICANCE
					:	0	.7833874	92.524	10	.0000
1*	.27651	100.00	100.00	.4654166	:					

* MARKS THE 1 CANONICAL DISCRIMINANT FUNCTION(S) TO BE USED IN THE REMAINING ANALYSIS.

STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.36386
V2	-.44812
V3	.18136
V4	.98869
V5	.71745
V6	.10871
V7	-.06417
V8	.09331
V9	.03553
V10	.27587

UNSTANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.7266470+000
V2	-.8992361+000
V3	.6674396-001
V4	.7729252-001
V5	.5012500-001
V6	.7686566-002
V7	-.2644360-002
V8	.5527949-002
V9	.3103084-002
V10	.1475206-001
(CONSTANT)	-.7740520+001

CANONICAL DISCRIMINANT FUNCTIONS EVALUATED AT GROUP MEANS (GROUP CENTROIDS)

GROUP	FUNC 1
1	.23382
2	-1.17842

TEST OF EQUALITY OF GROUP COVARIANCE MATRICES USING BOX'S M

THE RANKS AND NATURAL LOGARITHMS OF DETERMINANTS PRINTED ARE THOSE OF THE GROUP COVARIANCE MATRICES.

GROUP LABEL	RANK	LOG DETERMINANT
1	10	27.311959
2	10	25.531086
POOLED WITHIN-GROUPS COVARIANCE MATRIX	10	27.375650

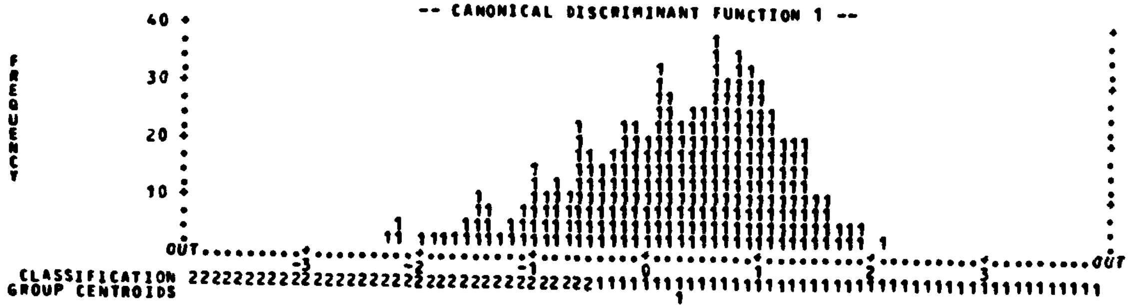
BOX'S M	APPROXIMATE F	DEGREES OF FREEDOM		SIGNIFICANCE
.13665+003	2.3401	55,	42032.9	.C000

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

HISTOGRAM FOR GROUP 1

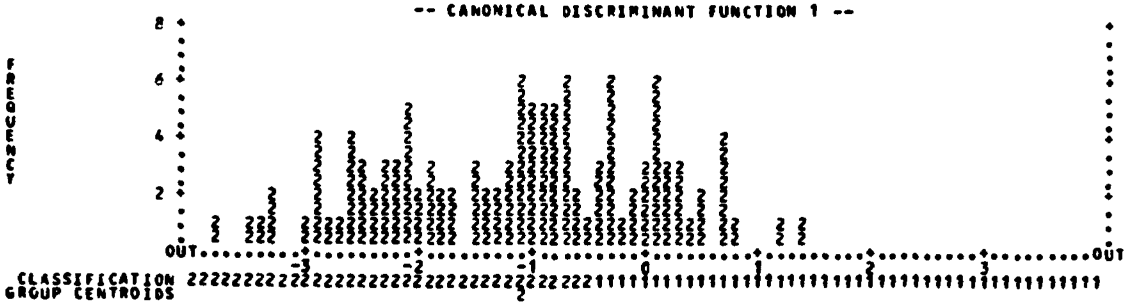
-- CANONICAL DISCRIMINANT FUNCTION 1 --



WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 24
WILKS-ALL VARS IN-EQUAL

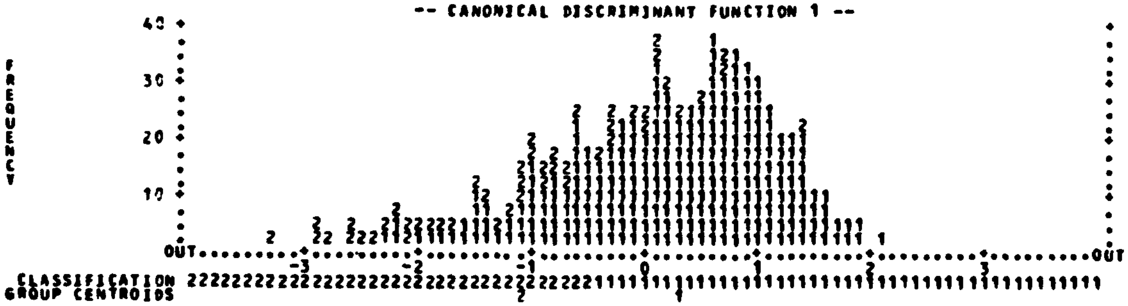
HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --



ALL-GROUPS STACKED HISTOGRAM

-- CANONICAL DISCRIMINANT FUNCTION 1 --



CLASSIFICATION RESULTS FOR CASES SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	398	312 78.4%	86 21.6%
GROUP	2	76	25 32.9%	51 67.1%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 76.58%

CLASSIFICATION RESULTS FOR CASES NOT SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	268	212 79.1%	56 20.9%
GROUP	2	42	13 31.0%	29 69.0%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 77.74%

CLASSIFICATION PROCESSING SUMMARY

784 CASES WERE PROCESSED.
0 CASES WERE EXCLUDED FOR MISSING OR OUT-OF-RANGE GROUP CODES.
784 CASES WERE USED FOR PRINTED OUTPUT.

APPENDIX E

LINEAR UNEQUAL (SIZE) *A PRIORI* CLASSIFICATION

```
WILLIAMS, 2-GROUP DISCRIM.                                        11/18/81        PAGE   26
WILKS-ALL VARS IN-EQUAL

CPU TIME REQUIRED..     2.36 SECONDS

         44.  TASK NAME        DIRECT-SIZE
         45.  DISCRIMINANT     GROUPS=GPS(1,2)/
         46.                   VARIABLES=V1,V2,V3,V4,V5,V6,V7,V8,V9,V10/
         47.                   SELECT=SET(0)/
         48.                   ANALYSIS=V1 TO V10/
         49.                   PRIORS=SIZE/
         50.  OPTIONS          2,5,7,8,9,10,11,12

THIS DISCRIMINANT ANALYSIS REQUIRES       702 WORDS OF WORKSPACE.
```

```
WILLIAMS, 2-GROUP DISCRIM.                                                        11/18/81        PAGE   28
DIRECT-SIZE
FILE    NONAME   (CREATION DATE = 11/18/81)

- - - - - - - - - - - - - - - - - - - -   D I S C R I M I N A N T   A N A L Y S I S   - - - - - - - - - - - - - - - - - - - -
ON GROUPS DEFINED BY GPS


ANALYSIS NUMBER        1

DIRECT METHOD:  ALL VARIABLES PASSING THE TOLERANCE TEST ARE ENTERED.

     MINIMUM TOLERANCE LEVEL..................   .00100

CANONICAL DISCRIMINANT FUNCTIONS

     MAXIMUM NUMBER OF FUNCTIONS..............        1
     MINIMUM CUMULATIVE PERCENT OF VARIANCE...   100.00
     MAXIMUM SIGNIFICANCE OF WILKS' LAMBDA....   1.0000

PRIOR PROBABILITIES

   GROUP     PRIOR      LABEL

       1    .83620
       2    .16380

   TOTAL   1.00000

CLASSIFICATION FUNCTION COEFFICIENTS
(FISHER'S LINEAR DISCRIMINANT FUNCTIONS)

GPS       =           1               2


V1                .2711767+002    .2814262+002
V2                .2654931+002    .2781737+002
V3                .5005431+000    .4064149+000
V4                .9404474+001    .9295472+001
V5                .2357064+000    .1650460+000
V6               -.3801171+000   -.3909571+000
V7               -.4695951-001   -.8323030-001
V8               -.3945941-001   -.4711615-001
V9                .8065856+000    .8022096+000
V10               .1998963+000    .1790923+000
(CONSTANT)       -.1111637+003   -.1025279+003
```

WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 29
DIRECT-SIZE

CANONICAL DISCRIMINANT FUNCTIONS

FUNCTION	EIGENVALUE	PERCENT OF VARIANCE	CUMULATIVE PERCENT	CANONICAL CORRELATION	:	AFTER FUNCTION	WILKS' LAMBDA	CHI-SQUARED	D.F.	SIGNIFICANCE
					:	0	.7833874	92.524	10	.0000
1*	.27651	100.00	100.00	.4654166	:					

* MARKS THE 1 CANONICAL DISCRIMINANT FUNCTION(S) TO BE USED IN THE REMAINING ANALYSIS.

STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.36386
V2	-.44812
V3	.18136
V4	.08866
V5	.71745
V6	.10871
V7	-.06417
V8	.09331
V9	.03553
V10	.27587

UNSTANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.7266470+000
V2	-.8992361+000
V3	.6674594-001
V4	.7729252-001
V5	.5010500-001
V6	.7686566-002
V7	-.2644366-002
V8	.5427949-002
V9	.3103084-002
V10	.1675204-001
(CONSTANT)	-.7740520+001

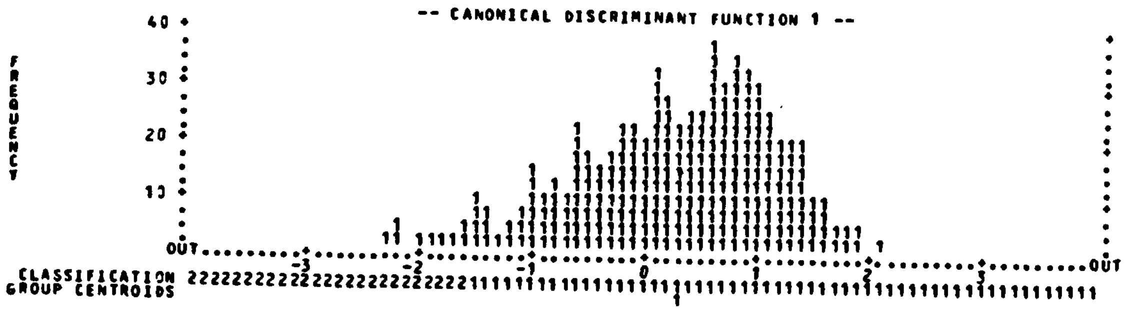
CANONICAL DISCRIMINANT FUNCTIONS EVALUATED AT GROUP MEANS (GROUP CENTROIDS)

GROUP	FUNC 1
1	.23382
2	-1.17642

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

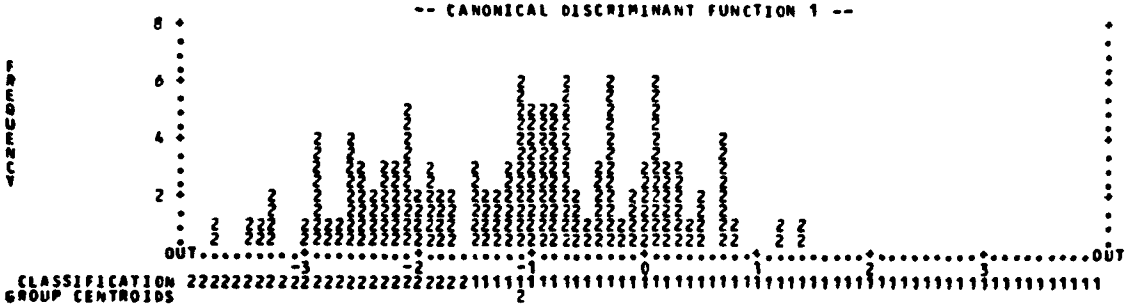
HISTOGRAM FOR GROUP 1



WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 31
DIRECT-SIZE

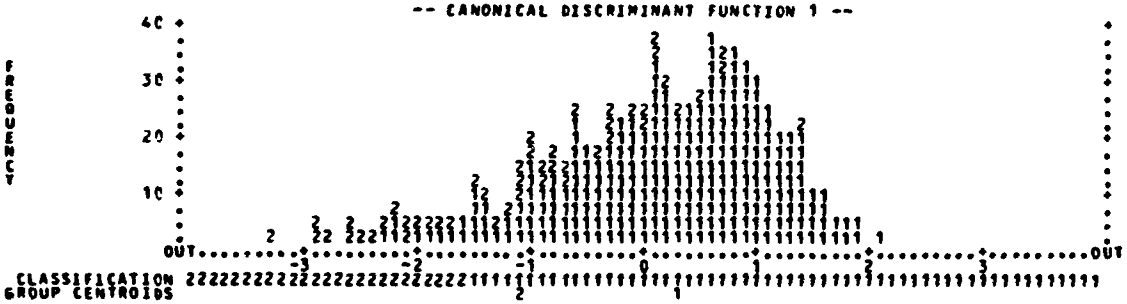
HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --



ALL-GROUPS STACKED HISTOGRAM

-- CANONICAL DISCRIMINANT FUNCTION 1 --



CLASSIFICATION RESULTS FOR CASES SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	398	383 96.2%	15 3.8%
GROUP	2	76	49 64.5%	27 35.5%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 86.50%

CLASSIFICATION RESULTS FOR CASES NOT SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	268	260 97.0%	8 3.0%
GROUP	2	42	28 66.7%	14 33.3%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 88.39%

CLASSIFICATION PROCESSING SUMMARY

784 CASES WERE PROCESSED.
0 CASES WERE EXCLUDED FOR MISSING OR OUT-OF-RANGE GROUP CODES.
784 CASES WERE USED FOR PRINTED OUTPUT.

APPENDIX F

QUADRATIC EQUAL *A PRIORI* CLASSIFICATION

```
DIRECT-SIZE

CPU TIME REQUIRED..    1.53 SECONDS

        51.  TASK NAME       QUAD-DIRECT-EQUAL
        52.  DISCRIMINANT    GROUPS=GPS(1,2)/
        53.                  VARIABLES=V1,V2,V3,V4,V5,V6,V7,V8,V9,V10, Z1 TO Z55/
        54.                  SELECT=SET(0)/
        55.                  ANALYSIS=V1 TO V10, Z1 TO Z55(2)/
        56.  OPTIONS         2,5,7,8,9,10,11,12

THIS DISCRIMINANT ANALYSIS REQUIRES     22262 WORDS OF WORKSPACE.
```

WILLIAMS, 2-GROUP DISCRIM.
QUAD-DIRECT-EQUAL
FILE NONAME (CREATION DATE = 11/18/81)

11/18/81 PAGE 35

- D I S C R I M I N A N T   A N A L Y S I S -

ON GROUPS DEFINED BY GPS

ANALYSIS NUMBER 1

DIRECT METHOD: ALL VARIABLES PASSING THE TOLERANCE TEST ARE ENTERED.

MINIMUM TOLERANCE LEVEL.................. .00100

CANONICAL DISCRIMINANT FUNCTIONS

MAXIMUM NUMBER OF FUNCTIONS.............. 1
MINIMUM CUMULATIVE PERCENT OF VARIANCE... 100.00
MAXIMUM SIGNIFICANCE OF WILKS' LAMBDA.... 1.0000

PRIOR PROBABILITY FOR EACH GROUP IS .50000

THE FOLLOWING 11 VARIABLES FAILED THE TOLERANCE TEST..

VARIABLE	WITHIN GROUPS VARIANCE	TOLERANCE	MINIMUM TOLERANCE
Z1	.250743+000	.0000000	.0000000
Z2	.500000	.0000000	.0000000
Z11	.248342+000	.0000000	.0000000
Z12	.107709+003	.0004060	.0003659
Z13	.411016+002	.0004040	.0003245
Z16	.166178+004	.0002691	.0002672
Z19	.131846+004	.0005534	.0005175
Z34	.615119+005	.0009917	.0007363
Z53	.313041+007	.0013329	.0006999
Z54	.398271+007	.0013966	.0007388
Z55	.564546+007	.0034657	.0008135

WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 36
QUAD-DIRECT-EQUAL

CLASSIFICATION FUNCTION COEFFICIENTS
(FISHER'S LINEAR DISCRIMINANT FUNCTIONS)

GPS =	1	2
V1	.1229260+004	.1240157+004
V2	.1786964+004	.1799282+004
V3	.4574309+003	.4563549+003
V4	.2703911+004	.2704078+004
V5	.4254755+002	.4259583+002
V6	.3859798+002	.3817780+002
V7	-.3689522+002	-.3679628+002
V8	.8348992+001	.8237881+001
V9	.9094483+002	.9097656+002
V10	.2062001+002	.2054107+002
Z3	-.1151156+002	-.1155916+002
Z4	.6236949+002	.6255684+002
Z5	-.1029242+002	-.1043976+002
Z6	-.6417919+001	-.6350657+001
Z7	.3681729+001	.3693327+001
Z8	-.7325714+001	-.7339282+001
Z9	-.2554855+000	-.2708631+000
Z10	-.1718225+001	-.1761502+001
Z14	-.1017072+002	-.1025447+002
Z15	-.7733267+001	-.7775970+001
Z16	.2887631+001	.2842475+001
Z17	-.7682614+001	-.7683504+001
Z20	-.1940882+001	-.1931806+001
Z21	-.2282858+002	-.2286571+002
Z22	.3520346+000	.3116187+000
Z23	.3557416+000	.3692556+000
Z24	.9535108+000	.9551273+000
Z25	.2651979+000	.2572369+000
Z26	-.2159232+001	-.2156043+001
Z27	-.1202002+000	-.1145048+000
Z28	-.6193286+002	-.6200519+002
Z29	-.2693037+001	-.2613276+001
Z30	-.4637503+001	-.4667329+001
Z31	.6767956+000	.6674444+000
Z32	-.3760679+000	-.3422093+000
Z33	-.2482477+000	-.2616698+000
Z35	.1062774+000	.1059829+000
Z36	.1232819+000	.1201327+000
Z37	.5674845-001	.5696977-001
Z38	-.6339937-002	-.5558258-002
Z39	-.4095404+000	-.4078592+000
Z40	-.5420209-001	-.5320222-001
Z41	.3193418+000	.3188854+000
Z42	-.1945776+000	-.1918980+000
Z43	.1265751-001	.1568508-001
Z44	-.2596591+000	-.2592416+000
Z45	-.1014730+000	-.1027636+000
Z46	.1985928-002	.8025036-003
Z47	.6002189-001	.5949047-001

CLASSIFICATION FUNCTION COEFFICIENTS
(FISHER'S LINEAR DISCRIMINANT FUNCTIONS)

GPS =	1	2
Z48	.1553505+000	.1537485+000
Z49	.5216036-001	.5223826-001
Z50	.2412024-002	.1626872-002
Z51	.4612624-001	.4281800-001
Z52	-.1159551+000	-.1165627+000
(CONSTANT)	-.1519808+005	-.1518150+005

CANONICAL DISCRIMINANT FUNCTIONS

FUNCTION	EIGENVALUE	PERCENT OF VARIANCE	CUMULATIVE PERCENT	CANONICAL CORRELATION	:	AFTER FUNCTION	WILKS' LAMBDA	CHI-SQUARED	D.F.	SIGNIFICANCE
1*	.43429	100.00	100.00	.5502648	:	0	.6972086	128.76	54	.0000

* MARKS THE 1 CANONICAL DISCRIMINANT FUNCTION(S) TO BE USED IN THE REMAINING ANALYSIS.

STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-3.08733
V2	-3.47322
V3	1.65456
V4	-.10877
V5	-.39118
V6	1.76196
V7	-1.79600
V8	1.08068
V9	-.20562
V10	.82676
Z3	.28054
Z4	-.68183
Z5	3.33207
Z6	-1.37675
Z7	-.21197
Z8	.30200
Z9	.35596
Z10	.91749
Z14	2.96810
Z15	.85885
Z16	-.61536
Z17	.01927
Z20	-.61317
Z21	-.69759
Z22	1.71404

	FUNC 1
Z23	-2.87002
Z24	-.47595
Z25	1.82542
Z26	-.22214
Z27	-1.37033
Z28	1.27084
Z29	1.20164
Z30	1.08608
Z31	1.31391
Z32	-4.63695
Z33	-.65372
Z35	-2.05403
Z36	3.21742
Z37	-.29761
Z38	-.86997
Z39	-1.62717
Z40	-1.17938
Z41	.52172
Z42	-1.62225
Z43	-3.21546
Z44	-.72598
Z45	1.54617
Z46	1.79439
Z47	.64679
Z48	2.07574
Z49	-.13649
Z50	1.02360
Z51	3.39180
Z52	.66613

UNSTANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.6145495+001
V2	-.6969396+001
V3	.8085153+000
V4	-.9481998-001
V5	-.2731890-001
V6	.1245821+000
V7	-.7409913-001
V8	.6280751-001
V9	-.1795775-001
V10	.4420985-001
Z3	.2693509-001
Z4	-.1040800+000
Z5	.7826961-001
Z6	-.3805723-001
Z7	-.9393429-002
Z8	.7677068-002
Z9	.8089406-002
Z10	.2448651-001

WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 39
QUAD-DIRECT-EQUAL

	FUNC 1
Z14	.7001606-001
Z15	.2416126-001
Z16	-.1971454-001
Z17	.5035714-003
Z20	-.5134949-002
Z21	-.1293682-001
Z22	.4761779-002
Z23	-.7929173-002
Z24	-.9032936-003
Z25	.4505510-002
Z26	-.6729914-003
Z27	-.3222502-002
Z28	.6092613-001
Z29	.5793258-002
Z30	.5559242-002
Z31	.6159339-002
Z32	-.1915743-001
Z33	-.3834956-002
Z35	-.9650174-003
Z36	.1781804-002
Z37	-.1252275-003
Z38	-.4422793-003
Z39	-.9512379-003
Z40	-.5657315-003
Z41	.2593452-003
Z42	-.1516115-002
Z43	-.1826181-002
Z44	-.4059270-003
Z45	.7302735-003
Z46	.6711174-003
Z47	.3006789-003
Z48	.9064054-003
Z49	-.5539266-004
Z50	.4462444-003
Z51	.1871828-002
Z52	.3637533-003
(CONSTANT)	-.9971901+001

CANONICAL DISCRIMINANT FUNCTIONS EVALUATED AT GROUP MEANS (GROUP CENTROIDS)

GROUP	FUNC 1
1	.29304
2	-1.47435

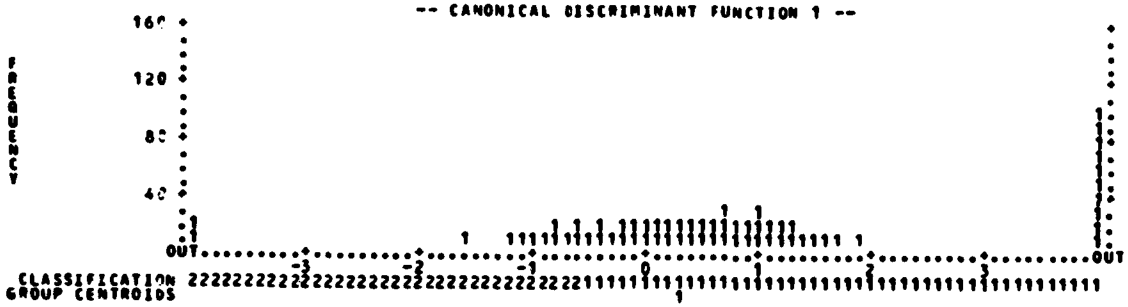
WILLIAMS, 2-GROUP DISCRIM.   11/18/81   PAGE 40
QUAD-DIRECT-EQUAL

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

HISTOGRAM FOR GROUP 1

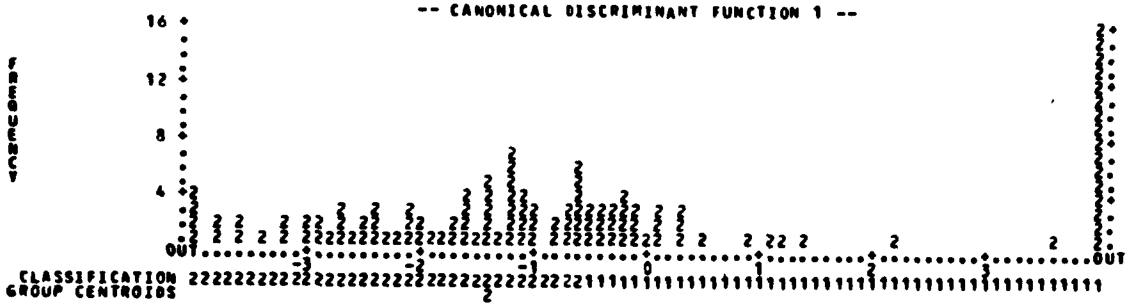
-- CANONICAL DISCRIMINANT FUNCTION 1 --



WILLIAMS, 2-GROUP DISCRIM. 11/18/81 PAGE 41
QUAD-DIRECT-EQUAL

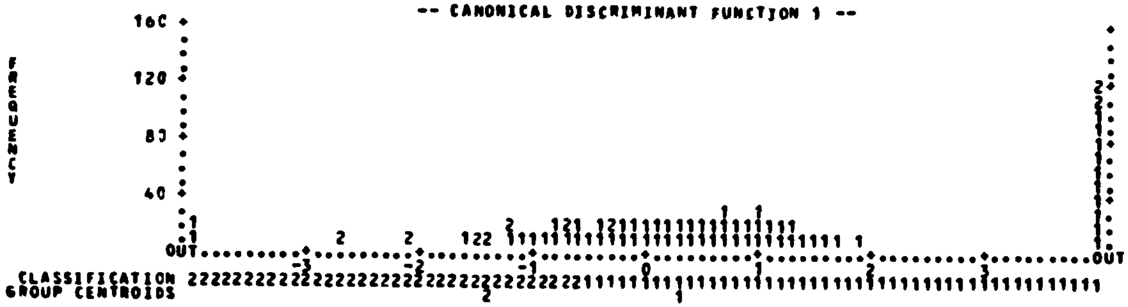
HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --



ALL-GROUPS STACKED HISTOGRAM

-- CANONICAL DISCRIMINANT FUNCTION 1 --



CLASSIFICATION RESULTS FOR CASES SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	398	337 84.7%	61 15.3%
GROUP	2	76	29 38.2%	47 61.8%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 81.01%

CLASSIFICATION RESULTS FOR CASES NOT SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP		NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP	1	268	215 80.2%	53 19.8%
GROUP	2	42	18 42.9%	24 57.1%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 77.10%

CLASSIFICATION PROCESSING SUMMARY

784 CASES WERE PROCESSED.
0 CASES WERE EXCLUDED FOR MISSING OR OUT-OF-RANGE GROUP CODES.
784 CASES WERE USED FOR PRINTED OUTPUT.

APPENDIX G

SUBSIDIARY ANALYSIS

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WILLIAMS, 2-GROUP DISCRIM.                                        11/23/81        PAGE    2

TRANSPACE REQUIRED..        120 WORDS
        4 TRANSFORMATIONS
        0 RECODE VALUES + LAG VARIABLES
       36 IF/COMPUTE OPERATIONS


               12.  TASK NAME          SUBSIDIARY ANALYSIS
               13.  DISCRIMINANT       GROUPS=GPS(1,2)/
               14.                     VARIABLES=V1,V2,V3,V4,V5,V6,V7,V8,V9,V10/
               15.                     SELECT=SET(0)/
               16.                     ANALYSIS=V1 TO V10/
               17.  OPTIONS            5,7,8,9,10,11,12
               18.  STATISTICS         1,2,3,4,6,7,9

THIS DISCRIMINANT ANALYSIS REQUIRES        986 WORDS OF WORKSPACE.
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\- D I S C R I M I N A N T   A N A L Y S I S -

ON GROUPS DEFINED BY GPS

641 (UNWEIGHTED) CASES WERE PROCESSED.
253 OF THESE WERE EXCLUDED FROM THE ANALYSIS.
0 HAD MISSING OR OUT-OF-RANGE GROUP CODES.
0 HAD AT LEAST ONE MISSING DISCRIMINATING VARIABLE.
0 HAD BOTH.
253 WERE EXCLUDED BY THE SELECT= VARIABLE.
388 (UNWEIGHTED) CASES WILL BE USED IN THE ANALYSIS.

NUMBER OF CASES BY GROUP

GPS	NUMBER OF CASES UNWEIGHTED	WEIGHTED	LABEL
1	332	332.0	
2	56	56.0	
TOTAL	388	388.0	

GROUP MEANS

GPS	V1	V2	V3	V4	V5	V6	V7	V8
1	.50602	.46?84	20.42169	12.69?60	86.43373	70.60843	55.40964	74.92470
2	.41071	.57143	20.00000	12.75000	68.75000	58.83929	40.17857	68.12500
TOTAL	.49227	.47680	20.36082	12.70619	83.88144	68.90979	53.21134	73.94330

GPS	V9	V10
1	81.09337	72.15361
2	7?.21429	56.60714
TOTAL	79.95619	69.90979

WILLIAMS, 2-GROUP DISCRIM. 11/23/81 PAGE 4
SUBSIDIARY ANALYSIS

GROUP STANDARD DEVIATIONS

GPS	V1	V2	V3	V4	V5	V6	V7	V8
1	.50672	.49922	2.90378	1.12091	11.60914	15.15649	24.82995	16.13979
2	.49642	.49935	2.49363	1.01354	18.71727	9.84937	18.63438	17.87742
TOTAL	.50059	.50011	2.84913	1.10496	14.27512	15.08031	24.60461	16.55129

GPS	V9	V10
1	11.59906	17.57893
2	10.28636	17.05591
TOTAL	11.73879	18.31901

POOLED WITHIN-GROUPS COVARIANCE MATRIX WITH 386 DEGREES OF FREEDOM

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2501076+000							
V2	-.2346232+000	.2492364+000						
V3	-.2184965-002	.3492727-001	.8116487+001					
V4	-.2499376-001	.2094388-001	.1229453+001	.1223781+001				
V5	.4038408+000	-.3221799+000	-.2649541+001	-.2623447-001	.1654872+003			
V6	.1677709+000	.1568004-001	.4711967+001	.6051642+000	.7081641+002	.2108100+003		
V7	.2152165+000	-.2173312-001	.2022411+001	.3509426+000	.7415418+002	.1923623+003	.5781567+003	
V8	.2481233+000	-.2196610-001	.1050315+000	.1609378+001	.5354817+002	.6604491+002	.2308029+002	.2689151+003
V9	.1745717+000	-.3145929-001	.1784787+001	-.4369499+000	.5351698+002	.1302929+003	.1297906+003	.6687781+002
V10	.1613597-001	.1271203+000	-.1351052+001	-.9252294+000	.8241549+002	.1906851+003	.2731504+003	.2771396+002

	V9	V10
V9	.1304496+003	
V10	.1150491+003	.3064521+003

WILLIAMS, 2-GROUP DISCRIM.
SUBSIDIARY ANALYSIS

POOLED WITHIN-GROUPS CORRELATION MATRIX

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
V1	1.00000									
V2	-.93973	1.00000								
V3	-.00153	.02456	1.00000							
V4	-.04518	.03792	.58048	1.00000						
V5	.06277	-.05017	-.07229	-.00184	1.00000					
V6	.02566	.00216	.11391	.03768	.37915	1.00000				
V7	.01790	-.00181	.02952	.01319	.23973	.55100	1.00000			
V8	.03025	-.00268	.00225	.03872	.25384	.27739	.05853	1.00000		
V9	.03056	-.00552	.05485	-.03458	.36424	.78569	.47261	.35707	1.00000	
V10	.00164	.01455	-.02709	-.04776	.36597	.75022	.64893	.09654	.57541	1.00000

CORRELATIONS WHICH CANNOT BE COMPUTED ARE PRINTED AS 99.0.

WILKS' LAMBDA (U-STATISTIC) AND UNIVARIATE F-RATIO
WITH 1 AND 366 DEGREES OF FREEDOM

VARIABLE	WILKS' LAMBDA	F	SIGNIFICANCE
V1	.99551	.1740+001	.1879
V2	.99395	.2351+001	.1260
V3	.99729	.1050+001	.3062
V4	.99973	.1027+000	.7488
V5	.80999	.9055+002	.0000
V6	.92459	.3143+002	.0000
V7	.95255	.1923+002	.0000
V8	.97910	.6239+001	.0043
V9	.94422	.2260+002	.0000
V10	.91083	.3779+002	.0000

TOTAL COVARIANCE MATRIX WITH   387 DEGREES OF FREEDOM

	V1	V2	V3	V4	V5	V6	V7	V8
V1	.2505861+000							
V2	-.2353219+000	.2501056+000						
V3	.2797091-002	.2906311-001	.8117531+001					
V4	-.2553345-001	.2159658-001	.1622052+001	.1220944+001				
V5	.6114541+000	-.5634606+000	-.1719385+001	-.1382829+000	.2037792+003			
V6	.3261741+000	-.1455097+000	.5314286+001	.5289832+000	.9640271+002	.2274156+003		
V7	.3944032+000	-.2302272+000	.2812435+001	.2534697+000	.1073119+003	.2140605+003	.6053867+003	
V8	.3277258+000	-.1150137+000	.4597865+000	.1562109+001	.6829817+002	.7578299+002	.3584406+002	.2739451+003
V9	.2671022+000	-.1392618+000	.2191561+001	-.4857748+000	.7063045+002	.1414379+003	.1443142+003	.7333859+002
V10	.1995591+000	-.6607715-001	-.5356427+000	-.1021404+001	.1162425+003	.2128471+003	.3017633+003	.4073131+002

	V9	V10
V9	.1377991+003	
V10	.1299165+003	.3355662+003

WILLIAMS, 2-GROUP DISCRIM. 11/23/81 PAGE 7
SUBSIDIARY ANALYSIS
FILE NONAME (CREATION DATE = 11/23/81)

- D I S C R I M I N A N T   A N A L Y S I S -

ON GROUPS DEFINED BY GPS

ANALYSIS NUMBER 1

DIRECT METHOD: ALL VARIABLES PASSING THE TOLERANCE TEST ARE ENTERED.

MINIMUM TOLERANCE LEVEL.................. .00100

CANONICAL DISCRIMINANT FUNCTIONS

MAXIMUM NUMBER OF FUNCTIONS.............. 1
MINIMUM CUMULATIVE PERCENT OF VARIANCE... 100.00
MAXIMUM SIGNIFICANCE OF WILKS' LAMBDA.... 1.0000

PRIOR PROBABILITY FOR EACH GROUP IS .50000

CLASSIFICATION FUNCTION COEFFICIENTS
(FISHER'S LINEAR DISCRIMINANT FUNCTIONS)

GPS =	1	2
V1	.3140975+002	.3240259+002
V2	.3095825+002	.3222517+002
V3	.2326624+000	.7827502-001
V4	.1094163+002	.1120775+002
V5	.3757968+000	.2799711+000
V6	-.5335173+000	-.5326898+000
V7	-.1165911+000	-.1150471+000
V8	.6577863-002	-.1986854-002
V9	.8834587+000	.8947514+000
V10	.2522289+000	.2267947+000
(CONSTANT)	-.1271309+003	-.1195347+003

CANONICAL DISCRIMINANT FUNCTIONS

FUNCTION	EIGENVALUE	PERCENT OF VARIANCE	CUMULATIVE PERCENT	CANONICAL CORRELATION	:	AFTER FUNCTION	WILKS' LAMBDA	CHI-SQUARED	D.F.	SIGNIFICANCE
					:	0	.7823285	93.528	10	.0000
1*	.27824	100.00	100.00	.4665528	:					

* MARKS THE 1 CANONICAL DISCRIMINANT FUNCTION(S) TO BE USED IN THE REMAINING ANALYSIS.

STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.33106
V2	-.42248
V3	.29379
V4	-.19665
V5	.82340
V6	-.00803
V7	.07157
V8	.09361
V9	-.06638
V10	.29740

UNSTANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS

	FUNC 1
V1	-.6631681+000
V2	-.8462492+000
V3	.1031236+000
V4	-.1777589+000
V5	.6400729-001
V6	-.5527391-003
V7	.2976398-002
V8	.5720848-002
V9	-.7563235-002
V10	.1698888-001
(CONSTANT)	-.5626390+001

CANONICAL DISCRIMINANT FUNCTIONS EVALUATED AT GROUP MEANS (GROUP CENTROIDS)

GROUP	FUNC 1
1	.21608
2	-1.26103

TEST OF EQUALITY OF GROUP COVARIANCE MATRICES USING BOX'S M

THE RANKS AND NATURAL LOGARITHMS OF DETERMINANTS PRINTED ARE THOSE OF THE GROUP COVARIANCE MATRICES.

GROUP LABEL	RANK	LOG DETERMINANT
1	10	26.921565
2	10	26.109668
POOLED WITHIN-GROUPS COVARIANCE MATRIX	10	27.096648

BOX'S M	APPROXIMATE F	DEGREES OF FREEDOM		SIGNIFICANCE
.11224+003	1.9053	55,	31259.5	.0001

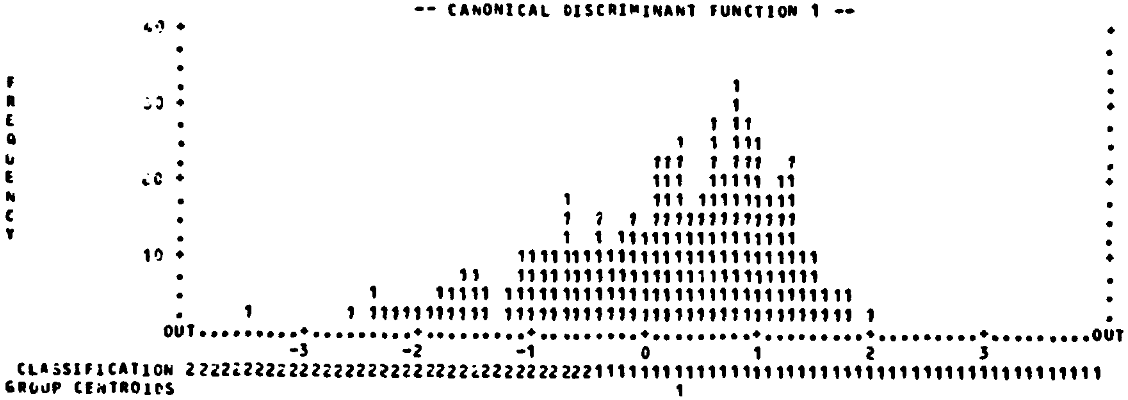
WILLIAMS, 2-GROUP DISCRIM. 11/23/81 PAGE 10
SUBSIDIARY ANALYSIS

SYMBOLS USED IN PLOTS

SYMBOL	GROUP	LABEL
1	1	
2	2	

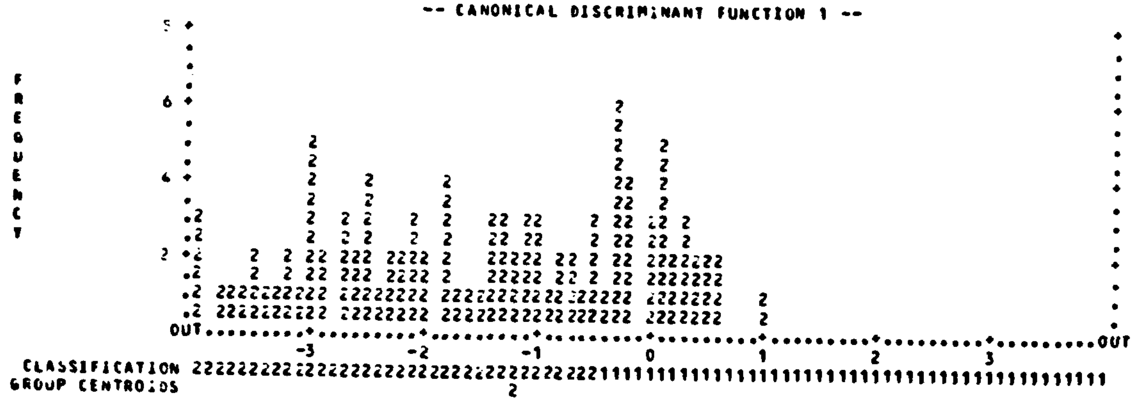
HISTOGRAM FOR GROUP 1

-- CANONICAL DISCRIMINANT FUNCTION 1 --



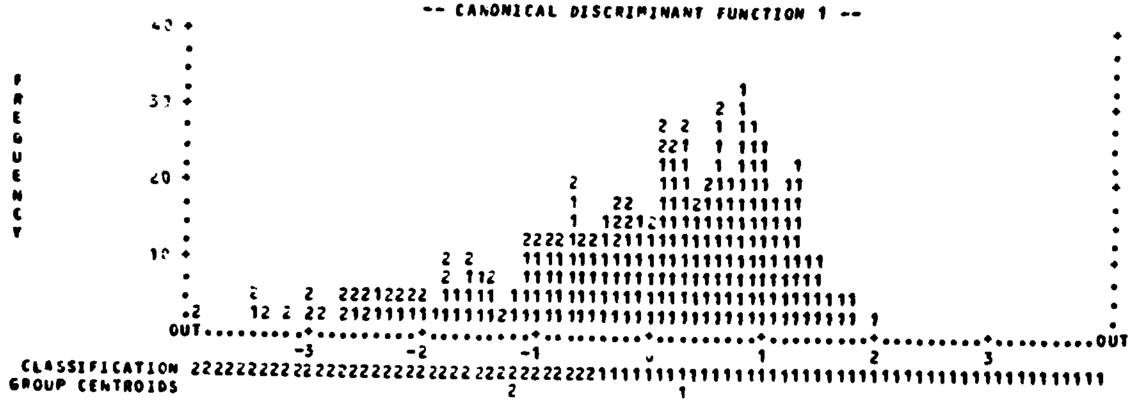
HISTOGRAM FOR GROUP 2

-- CANONICAL DISCRIMINANT FUNCTION 1 --



ALL-GROUPS STACKED HISTOGRAM

-- CANONICAL DISCRIMINANT FUNCTION 1 --



CLASSIFICATION RESULTS FOR CASES SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP	NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP 1	332	262 78.9%	70 21.1%
GROUP 2	56	22 39.3%	34 60.7%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 76.29%

CLASSIFICATION RESULTS FOR CASES NOT SELECTED FOR USE IN THE ANALYSIS -

ACTUAL GROUP	NO. OF CASES	PREDICTED GROUP MEMBERSHIP 1	2
GROUP 1	209	150 71.8%	59 28.2%
GROUP 2	44	12 27.3%	32 72.7%

PERCENT OF 'GROUPED' CASES CORRECTLY CLASSIFIED: 71.94%

CLASSIFICATION PROCESSING SUMMARY

641 CASES WERE PROCESSED.
0 CASES WERE EXCLUDED FOR MISSING OR OUT-OF-RANGE GROUP CODES.
0 CASES HAD AT LEAST ONE MISSING DISCRIMINATING VARIABLE.
641 CASES WERE USED FOR PRINTED OUTPUT.

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